Consumption-based learning about brand quality

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Consumption-based learning about brand quality:

Essays on how private labels share and borrow reputation

Proefschrift ter verkrijging van de graad van doctor aan de Universiteit van Tilburg, op gezag van de rector magnificus, prof.dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op maandag 7 december 2009 om 16.15 uur door

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To Marta

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Contents

1 Introduction

The emergence of information economics (Nelson 1970; Stigler 1961) has drawn the attention of researchers in both economics (e.g. Johnson and Myatt 2006; Miller 1984) and business (e.g. Eckstein and Wolpin 1989; Narayanan and Manchanda 2009) to the role of uncertainty and learning in the decisions of economic actors. Learning in the context of economics has generally been defined as “the cognitive or non-cognitive processing of information signals by economic agents that leads to a direct or latent change in their economic behavior, or to a change of cognitive pattern that influences future learning processes” (Brenner 1999). Extant studies have mostly focused on economic agents’ learning about characteristics of a decision object, such as consumers’ learning about product attribute levels. A growing body of research shows that choices made by economic agents are not based on the actual state of affairs, but rather on their beliefs thereof. Moreover, those beliefs are held with uncertainty which, for risk-avoiding decision makers, will lower the objects’ utility. This uncertainty, however, can be reduced as agents learn (or increased as agents forget). It is this phenomenon of learning and, more specifically, how it shapes agents’ beliefs about objects and agents’ subsequent decisions to adopt (or not to adopt) those objects, that is central to this thesis.

A common approach to modeling learning in business and economics research is the Bayesian learning formulation (Erdem and Keane 1996; Miller 1984; Roberts and Urban

1988). This formulation specifies how consumers integrate their prior beliefs about objects with new information signals, using a Bayesian updating rule, and it is often embedded in purchase incidence or choice models concerning these objects. In quantitative marketing, Bayesian learning models have been applied in a host of interesting studies that vary in the agents who learn, in the nature of the objects and dimensions that these agents learn about, and in the information sources that their learning is based on. While some of these studies have considered learning by intermediaries or specialists (such as, e.g., Narayanan and Manchanda 2009; or Narayanan et al. 2005 studies on physician learning and drug-prescribing behavior), most studies focus on consumers. The object of learning is typically brand quality (an exception being Iyengar et al. 2007, who model consumer learning about their service usage level) . This learning about brand quality has been modeled for services, such as insurances (Israel 2005) and online grocery stores (Goettler and Clay 2009), as well as for products, like pharmaceuticals (Akcura et al. 2004; Camacho et al. 2008; Crawford and Shum 2005; Janakiraman et al. 2008; Narayanan and Manchanda 2009), ski resorts (Moeltner and Englin 2004) and packaged goods (Ackerberg 2003; Erdem and Keane 1996; Mehta et al. 2004; Shin et al. 2007). Taken together, these studies have shown that consumers may infer brand quality from prices (Erdem et al. 2009) and advertising (Ackerberg 2003) or from other forms of marketing communication, such as pharmaceutical detailing (Narayanan and Manchanda 2009). Most Bayesian learning models in marketing, however, have looked at brand consumption as the source of information about brand quality. This thesis fits into this research stream: it focuses on how consumers' brand consumption experiences allow them to learn about brand quality, and affect their brand choice behavior.

Extant research in this area has produced relevant insights for both academics and practitioners. For one, it is shown that consumption-based learning about brand quality is an important phenomenon that may substantially affect brand performance (choice, adoption) over time. Second, this learning phenomenon carries implications for the way brands are managed. In particular, learning is found to influence the payoffs from brand quality improvements (Mitra and Golder 2006) and product innovation (Narayanan and Manchanda 2009) or – on the negative side – the consequences of product harm crises (Van Heerde et al.

2007). Moreover, learning affects the impact of price promotions (Akcura et al. 2004; Erdem et al. 2008),free samples (Erdem 1998), and umbrella branding (Erdem 1998; Erdem and Sun 2002) – findings that brand managers can put to proper use. With the development of these insights, however, new questions and challenges have come to the fore.

Consumer learning is expected to be prevalent in 'turbulent' markets, that is, when brands are new to consumers or when they have important new features (Erdem and Keane 1996; Heilman et al. 2000). Indeed, numerous studies document the presence of learning in such markets, for instance in pharmaceuticals (e.g. Narayanan et al. 2005). However, it has been shown that learning also takes place in rather stable, mature categories such as ketchup (Erdem et al. 2008), yogurt (Ackerberg 2003), liquid laundry detergent (Erdem and Keane 1996; Erdem et al. 2004; Mehta et al. 2004), margarine, toilet paper (Erdem et al. 2004), toothpaste (Erdem 1998; Erdem and Sun 2002; Shin et al. 2007), and toothbrushes (Erdem 1998; Erdem and Sun 2002). The focus in this thesis will be on learning in such consumer packaged goods.

The evidence of consumer learning in mature contexts suggests of the presence of quality uncertainty. There are a number of reasons why consumers are not perfectly knowledgeable about quality of brands. For example numerous consumptions of the same brand may be required to completely resolve brand quality uncertainty (Darby and Karni 1973; Nelson 1970). This could be, as suggested by Erdem (1998), because the effects of brand quality may take time or multiple consumptions to materialize, as in the case of teeth whitening toothpaste. Or, it may be difficult for the consumer to isolate the quality of the brand from other confounding factors. With toothpaste, for instance, the cavity-fighting ability of a brand is difficult to assess, as there are many causes for cavities that can develop even if the toothpaste is relatively effective. Similar arguments can be constructed for other product categories. Hoch and Deighton (1989) state that "a beer consumer who follows Lowenbrau's suggestion that 'tonight is kind of special' and serves Lowenbrau, will have difficulty untangling the effect of the occasion from the effect of the brand." As another example, the impact of a detergent on clothing fabric can take time to materialize, and deterioration of the fabric's color or durability can be difficult to ascribe to a detergent's poor quality. But also in food categories, multiple attributes such as a brand's health impact, storability, or even taste assessment in different use contexts, can be the subject of ongoing learning.

Furthermore, consumers generally buy and consume products sequentially rather than simultaneously, hampering effective brand comparisons and therefore learning (Hoch and Ha 1986; Warlop et al. 2005). Posing an additional challenge, the memory of brand quality deteriorates over time, between consumption and purchase occasions (Mehta et al. 2004; Warlop et al. 2005). Learning can also persist in mature environments as consumers change their consumption patterns over the life cycle (Du and Kamakura 2006), and some of their knowledge may need to be updated or even replaced (Heilman et al. 2000). These examples suggest that consumers may, indeed, gradually learn about brand quality from their experiences in packaged goods categories. However, the examples also suggest that the degree of learning about these products may well vary across consumers and categories – an issue largely unexplored as of yet, and one that we touch upon in chapter two of this thesis.

It is important to note that the vast majority of studies focus on within-brand learning – that is, how information pertaining to a particular brand impacts consumer beliefs about that same brand. There may be instances, however, where one brand's quality is expected by the consumer to also carry information about the quality of other brands. This can be the case when consumers categorize brands into the same "mental category," or when brands share certain attributes that are accessible to consumers and perceived to be diagnostic (Janakiraman et al. 2008). In such a setting, consumers may use new information obtained for one brand, e.g. based on consumption experiences with that brand, to update their quality beliefs about the other brand. Such cross-brand learning appears conceptually close to within-brand spillovers between attributes of the same product (Bradlow et al. 2004), between products of the same brand within the same category (Balachander and Ghose 2003), and between products of the same brand in different categories (Erdem 1998; Erdem and Sun 2002). While the latter are quite well documented, cross-brand learning has not received any attention in the literature, aside from a recent study by Janakiraman et al. (2008) that looks at learning between an original drug and its generic version. This is an important gap, as cross-brand spillovers of consumption experiences may have far-reaching brand management consequences that differ greatly from within-brand learning principles.

The main contributions of this thesis are in the area of cross-brand learning. More specifically, we study cross-learning in the context of private label (PL) brands for consumer packaged goods. These brands, which are the retailers' own brands, as opposed to national brands (NBs) belonging to manufacturers, have gradually grown in popularity over the last decades and currently constitute a sizable portion of package goods sold: 16% in the United States (AC Nielsen 2005), 39.6% in the United Kingdom, 46% in Switzerland (Planet Retail 2007 p.7). Selling own brands allows retailers to cash in larger margins (Ailawadi and Harlam 2004), build power vis-à-vis manufacturers (Ailawadi 2001), and compete more effectively with hard discounters (Boston Consulting Group 2004). The success of PLs constitutes a challenge for NBs, which once dominated packaged goods markets (Steenkamp and Dekimpe 1997).

Research on private labels stresses the importance of perceived brand quality in determining consumer private label usage (Ailawadi et al. 2003a; Dhar and Hoch 1997; Hoch and Banerji 1993; Steenkamp and Dekimpe 1997). Not only the perceived quality *level* of private labels is suggested to play a role, but also the degree of quality uncertainty (Batra and Sinha 2000; Erdem et al. 2004). While the importance of consumer beliefs about private labels' quality is well established, less is known about how consumers build these beliefs, particularly when it comes to learning processes, which set private labels apart from national brands.

In this thesis we study two different instances of cross-brand learning involving private labels. First, we investigate consumption spillovers across private label brands of different (rival) retailers, which may be perceived by consumers as similar to one another (Ailawadi 2001; Richardson 1997). Second, we explore the nature and impact of consumption-based cross-learning between leading NBs and copycat PLs that imitate their package design (Kapferer 1995; Sayman et al. 2002; Scott-Morton and Zettelmeyer 2004).

All studies included in the thesis employ a Bayesian learning model. In essence, the choice model including Bayesian learning is an extension of a traditional brand choice model featuring brand intercepts, marketing mix variables, and an error term. Traditionally, brand intercepts are constant over time and capture consumers' average utility from a brand when other variables equal zero. In the Bayesian learning model, the intercept is not restricted to be constant over time. Instead, consistent with information economics theory, the intercept is argued to capture the evolution of a consumer's beliefs about the true quality of a brand. The household's quality belief, captured by the intercept, is broken down into two parts, one referring to the *level* of the quality belief and one capturing the *uncertainty* in the consumer's quality belief. Both of these values evolve over time as consumers learn about true brand quality and forget earlier acquired knowledge.

In applications allowing for consumer specific true brand quality, like ours, the true quality of a brand is defined as an aggregate representation of the fit between the positioning of the brand across brand attributes on the one hand, and the consumer's preferences on the other. Thus, it does not equal the "objective quality" about which one could learn for instance through tests by Consumer Reports. It is consumer specific, and depends on both objective levels of brand attributes and individual consumer preferences for these attribute levels.

The model allows for learning from brand consumption. Each consumption experience can provide some information about the brand's true quality, but this information can be noisy e.g., as a result of variability in brand quality or of the consumer's inability to observe quality during consumption. If learning from consumption is indeed observed, we expect the level of perceived quality to gradually converge to the (consumer's) true brand quality, and the variance of the quality to diminish. The model also allows for consumer forgetting, which would entail a gradual increase in uncertainty over time. A Bayesian rule is used to reflect how consumers combine their current knowledge with the new information obtained through consumption. We describe this model, which has been used in previous literature, in detail in chapter 2 and our extensions of the model in chapters 3 and 4. In most applications of the Bayesian learning model, including ours, the researcher does not observe information signals obtained by the consumer from each consumption experience. Therefore, instead, the researcher specifies a distribution for these consumption signals (typically a normal density) of which the mean and variance are estimated, and then integrates over a large number of draws (possible consumption signals) implied by that distribution. Related to this, available scanner panel data typically only provide information on the timing of *purchases*, not of consumption experiences – the implicit assumption being that units will be consumed between one purchase and the next. In view of this, ‘purchase-based learning’ would be a more accurate description of what is captured by the model estimates. Still, to avoid confusion, we follow the literature in adopting the terminology ‘consumption-based learning’, while fully recognizing that our results – like those in previous research - provide only an approximation of this experience-based process.

Our main interest in this thesis is in consumers’ over-time (brand choice) reaction to aspects of retailers’ branding policy, namely: the quality positioning of their PL brand, the extent to which it is communicated to the consumers as being a private label, and whether or not it copycats a leading national brand. A challenge when studying these types of problems is that major shifts in those policies take place only sporadically, if ever. Moreover, if a policy change takes place (e.g. a brand policy change from copycatting to not copycatting), this often goes along with other changes (e.g. no longer imitating the national brand requires a change in the trade dress of the brand). This makes it difficult for the researcher to assess the impact of policy changes directly, and or to isolate this impact from other, co-occurring changes. Like previous researchers, we deal with this problem by focusing on variation in behavior of individual households. We can examine the presence and magnitude of specific consumer-level brand choice dynamics, which we argue are linked with the brand policies of interest. Subsequently, using simulations in which some aspects of the brand policies are altered, or comparing settings/brands for which different policies apply, we get a feel for their effect on the variables of interest, e.g. brand choice shares. Naturally, the absence of major over-time policy shifts in our data limits the strength of our conclusions: it requires us to limit our inferences to smaller changes (e.g. small quality positioning shifts) and/or to be cautious in making causal statements about the effect of major policy shifts.

Applications of Bayesian learning models make different assumptions about whether consumers maximize current utility, or are forward-looking. Current utility maximization means that a consumer chooses the brand with the highest expected utility. Forward-looking implies that consumers optimize their longer-horizon utility and may, for instance, choose brands strategically in order to learn about their quality and make better choices in the future. Previous literature suggests that the presence of forward-looking behavior depends on the context. For instance, Erdem and Keane (1996), having found no difference in predictive power of a current utility-maximization model and a forward-looking model, conclude that "forward looking models may be most useful in product categories where there is a substantial amount of uncertainty and, hence, the expected benefit associated with sampling different brands in order to learn about them is high". Given that our applications are for stable, fast moving consumer goods similar to those used by Erdem and Keane (1996), and given that accounting for forward-looking would make our already complicated cross-effect models even more complex, we decided not to include forward looking behavior for reasons of parsimony. The likely impact of such a restriction is that we do not take explorative purchases into account and therefore underestimate consumer dynamics. If this holds true, it would imply that our conclusions on the presence and strength of (cross) learning effects are conservative.

The thesis comprises five chapters. Chapter two is a "warm-up" chapter, which explores the magnitude and drivers of within-brand learning in a diverse set of packaged goods categories. This chapter sets the stage by making the reader familiar with the Bayesian learning model imbedded in a brand choice specification. We calibrate this household-level brand model in 20 categories of frequently purchase consumer products, and obtain category- and household-specific posterior estimates of the parameters indicating the extent to which consumers update their knowledge with new consumption-based information. From a substantive viewpoint, the chapter sheds some additional light on the prevalence and magnitude of learning for packaged goods, the variation in learning across categories and across households, and the underlying learning drivers. We find that learning is present and significant in almost all categories, yet varies in strength across categories and across households. Interestingly, we observe very low correlations between households' learning in different categories, suggesting that consumption-based knowledge updating is not a household trait. At the same time, we find that learning is negatively associated with variety seeking, positively linked to perceived category risk and category expensiveness, and more predominant among consumers with high category purchase frequency – observations that have face validity.

While chapter two fleshes out a familiar process (within-brand learning) using a well-established methodology (Bayesian quality-belief updating from same-brand consumption) by broadening the empirical evidence and exploring its underlying drivers, the main contributions of the thesis stem from chapters three and four. In these chapters, we focus on a phenomenon that has not been previously documented – across-brand consumption-based learning – and we introduce our novel hypotheses and provide empirical evidence using enhanced learning models. A common thread in these chapters is that consumers use consumption experiences with one brand to update their quality beliefs about another, and that at least one of the considered brands is a private label. Apart from these similarities, the chapters deal with very different realities that present quite different challenges and implications for retailers and manufacturers.

In chapter three, we study cross-brand learning among PL brands of different retailers. The study aims to bridge two views of private labels that seem present among academics and practitioners. One view holds that private labels are a way for retailers to differentiate themselves from competing chains. The opposite view is that private labels are "non-brands" (generic products) and that consumers do not differentiate between PLs offered by different retail chains. Our premise is that consumers learn across PL brands to a certain extent: we expect such cross-brand learning to be moderated by the perceived similarity between PL brands in terms of quality, with lower (higher) similarity being associated with weaker (stronger) cross-brand learning among rival chains' PLs. Moreover, we expect such cross-brand learning to evolve over time, as consumers develop more accurate beliefs about the quality of each PL brand. To test these expectations, we extend the traditional Bayesian learning model by including cross-brand learning contingent on perceived brand similarity. We use household scanner data from the liquid dish detergent category wherein we observe consumer brand choices and firm's marketing variables over time. Given our focus on consumption-based learning across PLs of different retailers, we focus on consumers who engage in purchases for this category in at least two chains. We use our model to infer how these consumers learn about brand quality from consumption, to what extent PL cross-brand learning takes place and how it depends on the PL brands' perceived similarity.

Our findings point to substantial cross-brand learning. Its dependence on perceived similarity is statistically significant, but a managerially meaningful decrease in cross-brand learning is observed only when brands are perceived to be very different from one another, that is, more different than the majority of sample households consider these brands to be. Our counterfactual simulations shed light on the implications of the unveiled cross-brand learning process. We show that it substantially reduces the potential of PLs to differentiate retailers in the eyes of multiple store shoppers. At the same time, we discover that PLs involved in cross-brand learning may gain market share vis-à-vis NBs. This is because learning about one PL brand from other PL brands reduces its uncertainty and, by doing so, increases its utility. Taken together, these findings carry an interesting caveat for retailers. If they aim to use their PLs to differentiate themselves from other chains, they need to set their quality markedly higher than that of other retailers. However, by doing so, they are likely to forego the benefits of cross-brand learning in terms of gaining market share from the NBs.

While chapter three considers consumption experience spillovers between PL brands, the fourth chapter takes a different angle: it deals with learning between a leading NB brand and a PL imitating its package design, and seeks to elucidate the extent to which the success of copycat private labels can be ascribed to the imitation strategy. Even though the copycat phenomenon is widespread, its over-time effects on the imitating brand are unclear, as little empirical evidence is available on its brand choice consequences, especially in actual choice settings. Moreover, generalizability of the extant copycat research to private label copycats is hampered by the fact that most of the present research focuses on "blunt" copies that also involve imitation of the original's brand name. The effect of such imitations is driven mostly by consumer brand confusion (Warlop and Alba 2004). PL copycats, by contrast, are seldom "blunt" imitations: they carry different names, and, though the trade-dress similarity is apparent, its difference from the copied original is still clearly noticeable. Such an imitation tactic is unlikely to lead to brand confusion (Warlop and Alba 2004). Yet, it may constitute a trigger for cross-brand learning. On the one hand, positive consumption experiences with the imitated national brand may enhance quality beliefs about the copycat PL, and entail a transfer of market share from the original NB to the copycat. Yet, at the same time, the imitation strategy can backfire on the retailer. If the quality gap between the original brand and imitating brand leads to contrast effects, the evaluation of the original brand can increase – the so-called "rewarding effect" (Zaichkowsky and Simpson 1996). Or, it can make consumers interpret the package similarity as an attempt on the part of the retailer to mislead them, and produce a "reactance effect" (Warlop and Alba 2004).

To assess these potential effects of copycatting, we specify a Bayesian learning model that incorporates both within-brand learning and across-brand learning among the original NB and the copycat PL brand, and accommodates possible post-consumption reactance or rewarding behavior. We calibrate the model on data from two product categories, powdered laundry detergent and liquid dish detergents, in two different chains. Our findings shed light on whether PL imitations constitute a 'friend' for the original NBs (ultimately rewarding the original brand for being superior in quality and hard to imitate) or a 'foe' (stealing market share by piggy-backing on its quality reputation). We find that the impact of copycatting on a brand's choice share is dominated by one-directional learning from the original brand to the copycat. This results in a reduction of quality uncertainty for the copycat and increases its choice share among risk-averse consumers. This choice share gain for the copycat mostly occurs at the expense of the original brand, and persists even after consumers become aware of the copycat's true quality – implying that copycat PLs predominantly constitute a 'foe' to their original NB counterparts.

Chapters two, three and four present the detailed underpinnings of these findings. Each chapter provides a conceptual framework pertaining to the issue at hand, and outlines the data and model specifics. Each chapter also contains a separate section with managerial implications. In chapter five, the concluding chapter of this thesis, we integrate the different findings, and place them in a broader perspective. We also point to remaining caveats and to new research angles to be addressed by future research.

2 Consumption-based learning in packaged goods: An exploratory multi-category study

2.1 Introduction

Traditional consumer behavior models (Pechmann and Ratneshwar 1992; Wright and Lynch 1995) as well as studies in the field of information economics (Miller 1984; Nelson 1970) argue that consumer choices over time are driven by uncertainty and learning. Consumption-based learning is expected to prevail in settings with ‘complex decision making’ (Narayanan et al. 2007), and in infrequently purchased, high involvement or strongly evolving categories such as insurance, pharmaceuticals, or telephone services (Akcura et al. 2004; Israel 2005; Narayanan et al. 2007; Narayanan and Manchanda 2009). However, recent evidence suggests that consumption-based quality learning can occur beyond these categories. Several studies report that consumers rely on consumption experiences to update their quality beliefs and adjust their brand choice in categories like ketchup, liquid laundry detergent, toothpaste and toothbrushes (Erdem 1998; Erdem et al. 2008; Mehta et al. 2004). From a managerial perspective, this phenomenon is important as it drives the effectiveness of brand quality improvements (Mitra and Golder 2006) or breakdowns (Van Heerde et al. 2007) and, indirectly, influences the impact of price promotions (Akcura et al. 2004; Erdem et al. 2008), free samples (Erdem 1998), product innovation (Narayanan and Manchanda 2009), and umbrella branding (Erdem 1998; Erdem and Sun 2002). Yet, available evidence on consumption-based learning in packaged goods is limited to just a few product categories, raising questions as to when this type of learning prevails. Broader knowledge would assist managers in their decisions on where and how to introduce strategies and tactics that rely on consumer learning.

Our study aims to address this knowledge gap. In particular, we are interested in the following research questions.

- Is consumption-based quality learning prevalent in consumer packaged goods (CPG) categories? Given that packaged goods categories are typically frequently purchased, low involvement, and mature categories in which consumers are expected to have some knowledge of brands, we are curious to see whether the CPG categories where learning was previously reported are an exception or a rule.

- How strong is learning in specific CPG categories and what are the differences in learning magnitude across categories? Estimating the amount of learning is important in judging the economic significance of the effect and, hence, its managerial relevance. Moreover, identifying categories where consumers learn the most can help manufacturers and retailers in the design of their marketing programs, by, for instance, offering more free samples in categories where consumption-based learning is stronger.

- Do all households learn? How heterogeneous are households in terms of learning magnitude, and is learning a universal or rather a fringe behavior?

- What are the drivers of consumption-based quality learning? Assessing the category- or household-related antecedents of this phenomenon not only enhances our understanding, but also guides managers in targeting their learning-related actions.

To address these questions, we use purchase data from a stable panel of 192 households in a major retail chain, covering purchases of the top 3 brands in 20 product categories over a period of 2.5 years. Our approach is similar to that of Nijs et al. (2001) and Bolton (1989) in that, for reasons of tractability, we conduct our analysis into two stages. In the first stage, we calibrate household-level brand choice models with Bayesian learning in each of these categories. We then obtain category- and household-specific posterior estimates of the consumption signal variance parameters, indicating the extent to which consumers update their knowledge on brand quality with new consumption-based information. Next, we use these estimates to assess the statistical significance and amount of learning, and establish to what extent it varies between categories and households. In the second stage, we use regression analysis to explore the link between the posterior learning parameters and a set of potential category- and household-related antecedents.

The remainder of the chapter is organized as follows. In the next section, we zoom in on the first stage of the analysis. We present the data and learning-based choice models, and report on the magnitude and co-variation of the estimated learning effects across households and categories. Section 3 then documents the approach and outcomes of the second stage. It introduces potential learning drivers, and tests their association with the estimated amount of consumption-based quality updating. Section 4 presents conclusions, discusses managerial implications, and indicates limitations and suggestions for future research.

2.2 Stage 1: Magnitude of consumption-based learning

In this section we discuss the first stage of our analysis. It is aimed at measuring the magnitude of consumption-based learning, and at exploring the learning co-variation, across households and categories.

2.2.1 Data

Our main data source consists of household panel data covering purchases made by a stable sample of 192 households in a major Dutch retail chain, across twenty product categories. The categories cover a wide range of items, from both the food and non-food supermarket sections. Households are selected so as to maximize the overlap across categories, while maintaining a minimum, yet sufficient, sample size in each category. While this procedure implies that our household sample is not strictly random, it has the important advantage of allowing for meaningful cross-category comparisons of household behavior, while ensuring parameter stability in each category. In particular, we focus on households that made a purchase in at least two categories. From this subgroup, we randomly select 100 households for each category (in categories where fewer than 100 households were left, we retain all those households in the final sample). Next, all households that are present in one category are also included in the other categories in which they made purchases. Finally, for categories with fewer than 100 selected households but where more households are available, we randomly draw additional households and also include them in all other categories in which they are present. In all, this final sample covers 43964 purchases across the twenty categories.

Our data include brand-level information on the quantities bought and the corresponding prices and promotions in the focal chain, over a period of 2.5 years. In each category, we consider the top three brands (for similar approaches see Chen and Yang 2007; Dekimpe et al. 1999; Nijs et al. 2007). Table 2.1 lists our sample categories together with the descriptive statistics for category brands. It indicates that categories vary in terms of concentration, with the top 3 brands' share ranging from 80% in the Vinegar category to 34% in the Liquid laundry detergent category. The price variation within categories, also, differs considerably, the highest-to-lowest price ratio ranging from 1.02 for Female hygiene and diapers, to 4.19 in the Cleaning materials category.

Table 2.1 also sheds light on the temporal variation in household brand choices. To construct this table, we divide the data into four 32 week-periods, and compute the choice shares for each brand per household and period. Next, we calculate the over-time standard deviation of those shares per brand and household. The figures suggest that in most categories, there are substantial consumer level dynamics, which do not appear to be entirely due to promotional activity as 47% of households who do buy PLs do not make any PL purchase during price promotion. The model developed in the next section will shed light on whether these dynamics are consistent with consumer consumption-based learning.

TABLE 2.1 DESCRIPTIVE STATISTICS FOR BRANDS IN SAMPLE CATEGORIES

Category	Brand	Choice share	Temporal variation in households' choice shares*	Number of purchases	Number of households	Average price	Share of households never buying a brand during promotion	Brand type
Spices and herbs	1	0.579	0.26	1117	127	6.536	0.496	Private label
	2	0.36	0.25	676	114	9.731	0.965	National Brand
	3	0.061	0.07	118	44	6.275	1.000	National Brand
Rice and pasta	1	0.453	0.2	1314	129	0.759	0.163	Private label
	2	0.275	0.17	816	119	0.746	0.286	National Brand
	3	0.273	0.2	825	122	0.724	0.320	National Brand
Liquid dish detergent	1	0.493	0.15	370	61	0.424	0.770	Private label
	2	0.443	0.12	293	50	0.498	0.220	National Brand
	3	0.064	0.11	81	19	0.407	0.474	National Brand
Dressing	1	0.365	0.17	2249	155	0.519	0.155	Private label
	2	0.372	0.12	2426	100	0.597	0.350	National Brand
	3	0.263	0.12	1808	112	0.338	0.125	National Brand
Milk substitutes	1	0.459	0.15	843	74	0.416	0.824	Private label
	2	0.107	0.09	224	26	0.308	0.808	National Brand
	3	0.433	0.13	758	75	0.528	0.653	National Brand
Mouth hygiene	1	0.395	0.12	245	31	1.532	0.516	Private label
	2	0.424	0.11	276	54	2.116	0.407	National Brand
	3	0.181	0.09	105	16	2.684	0.375	National Brand
Fish and seafood	1	0.673	0.22	1538	130	2.775	0.431	Private label
	2	0.168	0.15	378	89	2.652	0.169	National Brand
	3	0.159	0.14	398	75	1.75	0.573	National Brand
Warm drinks	1	0.439	0.18	3010	160	2.244	0.138	Private label
	2	0.087	0.07	576	73	3.073	0.384	National Brand
	3	0.474	0.18	3190	165	2.538	0.085	National Brand
Fabric softeners	1	0.527	0.18	253	41	0.313	0.146	Private label
	2	0.342	0.11	177	42	0.386	0.167	National Brand
	3	0.13	0.17	64	29	0.338	0.276	National Brand
Biscuits and cookies	1	0.671	0.17	5924	215	0.692	0.060	Private label
	2	0.139	0.09	1219	144	0.526	0.576	National Brand
	3	0.19	0.13	1609	176	0.78	0.119	National Brand

TABLE 2.1 CONTINUED

Category	Brand	Choice share	Temporal in household's in choice shares*	Number of purchases	Number of households	Average price	Share of households never buying a brand during promotion	Brand type
Bread substitutes	1	0.473	0.17	1137	97	0.657	0.474	Private label
	2	0.327	0.13	786	82	0.445	0.634	National Brand
	3	0.2	0.13	465	69	0.73	0.536	National Brand
Toilet and kitchen tissues	1	0.562	0.23	1674	146	50.046	0.322	Private label
	2	0.242	0.16	802	110	85.277	0.500	National Brand
	3	0.196	0.19	615	103	49.922	0.049	National Brand
Liquid laundry detergent	1	0.316	0.21	94	24	0.735	0.542	Private label
	2	0.34	0.16	101	24	0.795	0.292	National Brand
	3	0.343	0.15	106	20	1.004	0.100	National Brand
Female hygiene and	1	0.494	0.19	490	48	18.674	0.438	Private label
	2	0.233	0.14	236	47	18.711	0.213	National Brand
	3	0.273	0.16	281	48	18.492	0.167	National Brand
Cleaning materials	1	0.299	0.19	131	35	0.106	0.886	Private label
	2	0.476	0.16	214	40	0.18	0.575	National Brand
	3	0.225	0.17	111	38	0.043	1.000	National Brand
Cleaning materials	1	0.35	0.2	247	62	0.414	0.806	Private label
	2	0.267	0.17	190	55	0.526	0.509	National Brand
	3	0.382	0.2	289	73	0.484	0.370	National Brand
Vinegar	1	0.804	0.18	612	81	0.276	0.407	Private label
	2	0.046	0.11	35	22	0.417	0.909	National Brand
	3	0.15	0.15	113	38	0.284	0.737	National Brand
Solid dish detergent	1	0.185	0.17	69	21	1.026	0.762	Private label
	2	0.481	0.1	165	29	1.604	1.000	National Brand
	3	0.334	0.14	135	36	1.275	0.167	National Brand
Ice-cream	1	0.433	0.23	671	115	0.586	0.217	Private label
	2	0.321	0.18	480	104	0.751	0.308	National Brand
	3	0.246	0.18	375	86	0.619	0.244	National Brand
Deodorant	1	0.648	0.24	278	71	95.393	0.775	Private label
	2	0.244	0.18	123	43	78.939	0.977	National Brand
	3	0.107	0.14	59	25	232.671	0.760	National Brand

* Standard deviation of the household's brand, calculated over four 32-week sub periods, and then averaged over households visiting the chain.

2.2.2 Method development

Central to our study is the measure of consumption-based quality learning. Our approach to quantify this amount closely follows the available literature (e.g. Erdem and Keane 1996).

One of the parameters in this model, the variance of the consumption signal, reflects the amount of quality information conveyed by a single ‘consumption experience’ (to be specified below). This parameter is used as a measure of learning magnitude. Since we estimate a choice model for each product category and adopt a random effects specification to capture household heterogeneity, we can use the posterior parameters as household- and category-specific (Train 2003) measures of the learning magnitude.

Category-specific choice models with Bayesian learning

Model specification. The specification of our brand choice model builds on structural dynamic choice models proposed by Erdem and Keane (1996) and extended by Mehta et al. (2004). In these models, consumers select the brand from a category that maximizes their current utility, the utility of brand j in category c on purchase occasion t being given by:[1]

$$U_{jct} = f\left(Q_{jct}\right) + X_{jct}\beta_c + \varepsilon_{jct}, \qquad [2.1]$$

where Q_{jct} indicates the consumer’s quality beliefs about brand j on purchase occasion t, X_{jct} is a vector of utility determinants other than quality beliefs observed by both the researcher and the consumer, β_c are sensitivity parameters to those determinants, and ε_{jct} are i.i.d. extreme value distributed portions of utility unobserved by the researcher but observed by the consumer (for a complete overview of the notation, see Table A1.1 in the appendix). Like previous models (e.g. Crawford and Shum 2005; Narayanan and Manchanda 2009), quality beliefs enter the utility expression through a negative exponential function:

$$f\left(Q_{jct}\right) = -\exp\left(-r_c Q_{jct}\right), \qquad [2.2]$$

with (a non-negative) risk aversion coefficient r_c, which implies that consumers exhibit ‘constant’ risk aversion with respect to their uncertainty about the true quality of brands.

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[1] We drop the consumer subscript for clarity of exposition.

Consumers' quality belief about brand j in category c on purchase occasion t, Q_{jct}, is normally distributed with mean μ_{jct} and variance (or uncertainty) σ_{jct}^2. Given the distribution of Q_{jct}, and using [2,1], we can rewrite the expected utility of brand j in category c on purchase occasion t as (Narayanan and Manchanda (2009):

$$E\left[U_{jct} \mid I_t\right] = -\exp\left(-r_c\left(\mu_{jct} - r_c \frac{\sigma_{jct}^2}{2}\right)\right) + X_{jct}\beta_c + \varepsilon_{jct}. \qquad [2.3]$$

where I_t is the information available to the consumer at time t.

Similar to previous learning models, we assume that consumers do not know brands' true quality, and we model their learning from consumption. Consumption of each unit of quantity (e.g. gram) of brand j in category c in period t – 1, provides a new quality experience g_{jct}, which we assume to be i.i.d. normally distributed with mean equal to the true brand quality q_{jc} and variance σ_{gc}^2: $g_{jct} \sim N(q_{jct}, \sigma_{gc}^2)$. We denote a series of M_{ct} consumption units of brand j in category c at time t as $G_{jct} = \frac{\sum_{m=1}^{M_{ct}} g_{jctm}}{M_{ct}} \sim N\left(q_{jc}, \frac{\sigma_{gc}^2}{M_{ct}}\right)$.

Consumers' uncertainty is reduced gradually as they learn, but it can also increase again due to forgetting (Mehta et al. 2004). In the absence of consumption at t – 1, we expect σ_{jct}^2 to increase exponentially, $\sigma_{jct}^2 = \sigma_{jct-1}^2 * e^{b_c(w_{ct} - w_{ct-1})}$, where b_c is an estimated decay parameter for category c, and $w_{ct} - w_{ct-1}$ refers to the time elapsed between purchase occasions t and t – 1 in category c.

Like previous studies, we assume that on each occasion t in category c, the consumer adopts only one brand, such that $\sum_j d_{cjt} = 1$, where $d_{cjt} = 1$ if brand j in category c were chosen at t and 0 otherwise. We also assume that consumption of the brand bought at t – 1 takes place right before the purchase in t, such that at the time of the update in t, the consumer has not forgotten the consumption signals g_{cjtm}.

Consumption based learning is modeled using the conventional expression (e.g. de Groot 1970), consumers' mean quality belief of brand j in category c on purchase occasion t (μ_{jct}) and the variance of this quality belief (σ^2_{jct}) are then as follows:

$$\mu_{jct} = \left(\frac{\mu_{jct-1}}{\sigma^2_{jct-1} * e^{b*(w_{ct}-w_{ct-1})}} + \frac{d_{jct-1} G_{jct}}{\frac{\sigma^2_{gc}}{M_{ct}}} \right) * \left(\frac{1}{\sigma^2_{jct-1} * e^{b_c*(w_{ct}-w_{ct-1})}} + \frac{d_{jct-1}}{\frac{\sigma^2_{gc}}{M_{ct}}} \right)^{-1} \quad [2.4]$$

and

$$\sigma^2_{jct} = \left(\frac{1}{\sigma^2_{jct-1} * e^{b_c*(w_{ct}-w_{ct-1})}} + \frac{M_{ct} * d_{jct-1}}{\sigma^2_{gc}} \right)^{-1} \quad [2.5]$$

In essence, this new, updated, belief is a weighted sum of the prior quality belief (μ_{jct-1}) and the consumption signal (G_{jct}), with weights equal to the prior quality uncertainty (σ^2_{jct-1}) and the consumption signal variance (σ_{gc}^2), resp. As we elaborate more extensively below, σ_{gc}^2 is a model parameter that captures how much consumption based learning takes place in a given category (Please note that the subscript g indicates that this is the variance linked to the consumption signal G. The subscript c, in contrast, reflects that this variance is category-specific).Like previous studies, we assume that the consumption signal variance, σ_{gc}^2, is pooled across brands. It is important to note, however, that this does not imply that the magnitude of learning is the same for all brands. For instance, brands that are more established will experience weaker learning, to the extent that consumers' uncertainty about their quality, σ^2_{jct-1}, is lower than for new, less established brands – thereby placing more weight on the first term in [2.4].

Capturing the magnitude of learning

In the above model, the magnitude of learning is captured by the value of the consumption signal variance – that is, *relative to* the uncertainty in brand quality before the consumption takes place. As implied by Equation [2.4], when the variance of the consumption signal σ_{gc}^2 is smaller (larger) than the prior brand quality uncertainty σ_{jct-1}^2, the impact on the consumer's quality belief μ_{jct} of a new consumption signal g_{jct} is larger (smaller) than the impact of the consumer's prior beliefs. Hence, holding uncertiaty constant, the smaller (larger) the consumption signal variance, the stronger (weaker) learning from consumption.

For identification, we fix the prior quality uncertainty at time t=0 by setting it equal to 1 (see Erdem and Keane 1996; Mehta et al. 2004). Hence, the estimated value of the consumption signal variance (relative to this fixed value of one) is going to capture the magnitude of learning, and therefore constitutes the focal parameter in our study. For convenience, in the subsequent sections of this chapter we refer to this parameter as the 'learning parameter'.

An intuitive metric of the learning magnitude, based on this parameter, will be the weight of the consumption signal in the consumer's first update of his quality belief. For instance, when the prior uncertainty and the consumption signal variance are equal (i.e., $\sigma_{gc}^2 = \sigma_{jc0}^2$), the prior quality belief and the first consumption signal contribute equally (50% each) to the posterior quality belief – as can be seen in Equation [2.4]. As the consumption signal variance is larger (smaller), ceteris paribus, the share of the posterior quality belief based on the consumption experience becomes smaller (larger). Note that over time, as also indicated by Equation [2.5], consumers' quality uncertainty decreases as they learn from consumption whereas the consumption signal variance is constant. Therefore, disregarding forgetting, the magnitude of learning (i.e., the share of the quality belief based on the new consumption signal) decreases with each subsequent consumption.

Household differences. We accommodate unobserved household heterogeneity by using a random effects specification. Using i as a household indicator, the parameters $q_{jc,i}$ and $\beta_{c,i}$ are normally distributed, while $\sigma_{cg,\,i}$, $b_{c,i}$, and $r_{c,i}$ have lognormal distributions (to ensure positive values).

Estimation. For identification, in each of the category-specific models we fix the population mean of the true quality parameter of the first brand to zero, and, as indicated above, set the uncertainty regarding brand quality at the beginning of the sample period to 1 (i.e., $\sigma_{c0}^2 = 1$). Thus, the parameters of our random effects model are the listed population means and variances. We estimate the parameters using simulated maximum likelihood. The appendix 1 provides details pertaining to the log likelihood function and the estimation procedure (similar to Mehta et al. 2004).

Issues in cross-category comparisons of learning magnitude

Household- and category-specific learning parameters. The outcomes of the category-specific models allow us to assess the amount of learning for each household and category. Specifically, based on the estimated mixing distributions of the consumption signal variance by category, we can obtain a posterior estimate of this consumption signal variance for each sampled household in that category, following the approach indicated in Train (2003).

Consumption units. Our measure of learning pertains to the precision of the information contained in one consumption unit. For category comparisons, a crucial question then becomes how a consumption unit is defined. To enable meaningful cross-category assessments, we normalize the measurement units such that a category's 'consumption unit' in our model corresponds to the *average purchase volume, across consumers,* per purchase occasion in that category. More specifically, we specify the number of normalized units adopted by the household in category c at time t as $M_{ct} = M_{ct}^{*} * (\bar{M}_{c}^{*})^{-1}$ where M_{ct}^{*} is the number of 'original units' adopted by the household in category c at that time (e.g., 500 grams of coffee), and $\bar{M}_{c}^{*}$ the average number of original units adopted across all households and purchase occasions in category c (e.g., 250 grams, such that the normalized number of units becomes M_{ct} =2).

Note that in most categories, the normalization constant $\bar{M}_c^*$ by and large coincides with a 'standard' or most commonly adopted package size. In the second stage of the analysis, we also control for the fact that this average purchase quantity may last for a different length of time (that is, cover a different number of average consumption-weeks) in different categories. We elaborate on this control variable in Section 3.

Comparing estimates across data sets. In logit models estimated on different data sets the scale of the parameters depends on the variance of the error term in the utility function (Swait and Louviere 1993). Therefore, direct comparison of estimates across different data sets confounds the parameter with the scale. This problem can be avoided by comparing ratios of parameters because the scale cancels out (see e.g. Erdem et al. 2004). In our case, the consumption signal variance parameter estimates are in fact a ratio of the initial uncertainty variance (which we fix for identification) and the consumption signal variance, and hence are comparable across categories.

2.2.3 Results: The amount of consumption-based learning across households and categories

Below, we first report the estimation results of the category-specific choice models with Bayesian learning. Next, based on the posterior learning parameters, we analyze the degree of learning across categories. The last subsection then zooms in on the household level, and explores whether experience-based quality learning is a household trait.

Estimation results

Model fit. Table A1.2 in the appendix summarizes the fit statistics of the proposed Bayesian learning model in each category, compared to a benchmark model with no purchase dynamics. We find that, in each category, incorporation of the Bayesian learning mechanism into the brand choice model results in an improvement in the AIC and BIC statistics, suggesting that consumption-based learning about brand quality does take place in these categories (save for the Vinegar and the Dressing categories, where the AIC and BIC deteriorate slightly).

Learning parameter estimates. To take a closer look at the amount of learning occurring, we turn our attention to the consumption signal variance parameter, or learning parameter (the complete set of estimation results, for all categories and variables, can be found in the appendix, Table A1.3). As the learning parameter is log-normally distributed across households and this mixing distribution is asymmetric, we focus on the median rather than the mean as a summary statistic.

We find that the median value of the learning parameters, pooled across categories and households, is 3.7 (see Table 2.2). As noted above, the magnitude of this figure needs to be interpreted against the quality uncertainty at the beginning of the sample period, which is fixed to 1. The fact that this prior uncertainty is much smaller implies that when consumers update their brand quality beliefs, prior beliefs are much more influential than new information obtained through consumption. Still, the new, consumption-based information exerts a non-negligible influence. This influence is on average 27% for the consumer's first purchase and, for simplicity's sake assuming an absence of forgetting, it diminishes to 9% by the 10^{th} purchase. This suggests that for the average of household and category combinations, learning is substantial.

TABLE 2.2 DESCRIPTIVE STATISTICS OF LEARNING PARAMETERS

	Learning parameters for all observed household-category combinations	**Learning parameters per household (median across categories)**	**Learning parameters per category (median across households)**
N	1972	192	20
Mean	5.6	3.7	3.9
Median	3.7	3.6	3.1
Standard deviation	8.2	1.5	3.9
Minimum	1*e-14	4*e-14	2*e-14
Maximum	147.3	11.2	11.5

Comparing the standard deviation of the category-specific and household-specific learning parameters (third and fourth columns of Table 2.2), indicates that both dimensions are characterized by substantial variation. While the variation has the same order of magnitude (standard deviation of 1.5 and 3.9 respectively), we find more homogeneity in the learning parameters (standard deviation less than half as large) across categories than across households.

In which categories is learning most prevalent?

Table 2.3 lists our sample categories together with their median learning parameters, sorted from lowest to highest. To better illustrate the meaning of these parameters, we also indicate the new consumption signal's share of influence on the consumer's updated quality belief (versus the share of influence derived from prior quality beliefs). We find vast differences in learning magnitude across categories. The lowest learning parameter is close to zero and the highest is 14.6, implying that a household's first consumption signal has an influence on the quality belief ranging from 100% to 6.4%, whereas the 10^{th} signal for a given brand (in the absence of forgetting) has an influence ranging from 11% to 4.2%. This suggests that while, at least for some categories, learning is substantial initially, in the absence of forgetting its influence would diminish rapidly after a few experiences.

Somewhat surprisingly, categories with the strongest learning are mostly household care categories (e.g. dish detergent, laundry detergents and fabric softener), whereas categories with slow learning mostly include personal care categories (e.g. toilet and kitchen tissues, female hygiene and diapers) and food (e.g. rice and pasta, dressing). It seems that for the type of home care products that are studied here, consumers extract a lot of information on brand quality from their consumption experiences. The second stage of our analysis deals more extensively with factors determining the magnitude of consumer learning.

TABLE 2.3 COMPARISON OF LEARNING MAGNITUDE ACROSS CATEGORIES

Product category	Median learning parameter	Influence of the first consumption signal on quality belief	Influence of the 10th consumption signal on quality belief
Solid dish detergent	2.15E-14	100.00%	11.11%
Vinegar	3.54E-14	100.00%	11.11%
Liquid dish detergent	0.002	99.83%	11.11%
Fabric softeners	0.457	68.66%	10.57%
Liquid laundry detergent	0.784	56.05%	10.22%
Mouth hygiene	0.888	52.98%	10.11%
Milk substitutes	1.016	49.61%	9.98%
Biscuits and cookies	1.311	43.27%	9.70%
Cleaning materials	1.695	37.11%	9.35%
Deodorant	2.978	25.14%	8.35%
Fish and seafood	3.814	20.77%	7.80%
Cleaners	3.881	20.49%	7.76%
Ice-cream	4.028	19.89%	7.68%
Spices and herbs	5.288	15.90%	7.00%
Bread substitutes	6.491	13.35%	6.46%
Female hygiene and diapers	8.635	10.38%	5.67%
Warm drinks	9.642	9.40%	5.36%
Dressing	11.631	7.92%	4.85%
Rice and pasta	14.311	6.53%	4.29%
Toilet and kitchen tissues	14.631	6.40%	4.23%

Is learning a household trait?

Table 2.2 indicates that households, overall, tend to differ in their degree of consumption-based learning. A next question is whether a given household exhibits ‘consistent’ learning behavior across categories; is there substantial co-variation in households’ learning parameters for different products? To investigate this, we compute, for each category pair, the correlation in learning parameters across households that are active in both categories. The resulting correlation matrix is presented in table A1.4 in the appendix. This matrix shows, for each category pair, whether households that are relatively strong learners in one category are also strong learners in the other category. Interestingly, we find these correlations to be rather low. The mean absolute correlation is 0.19 (see Table A1.3 in the appendix). Moreover, out of the 210 correlations, close to half (104) are negative, with the average correlation amounting to only .005. This indicates that the degree of learning in different categories varies widely from household to household, and, hence, is not a consumer trait. While it is apparent that there is no clear clustering of the categories, it seems that food categories and non-food categories constitute two subgroups with higher within-group, and lower across-group, correlations. This suggests that some households are strong learners in food categories and others in non-food categories, with relatively few households that are strong learners for both food and non-food products. This finding, however, needs to be treated with caution as our category models were not estimated simultaneously and Ainslie and Rossi (1998) demonstrate that such an approach leads to underestimation in the cross-category correlations of model parameters.,

A key question for managers is: What drives these category and household differences? We turn to this topic next.

2.3 Stage 2: Drivers of learning magnitude

In this section, we explore the drivers of consumption-based learning. We first identify three dimensions along which learning is expected to vary and construct measures that tap into these dimensions. Next, we discuss the method used for this second stage of our analysis. Finally, we report on the effect of the learning drivers.[2]

2.3.1 Drivers of consumption-based quality learning: Data and variables

When selecting the variables to be included in the second stage model, we reflect on what drives consumers to exhibit stronger consumption-based learning about brand quality.

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[2] Our choice of a two-step procedure over a one-step procedure is driven by the computational demands of the latter option: a one-step procedure would require simultaneous estimation of both stages and all 20 category models, which is infeasible.

We expect the dimensions underlying this learning magnitude to be: the level of uncertainty, the consumers' incentives to learn, and variety seeking. Below we discuss each of these dimensions in more detail, and propose variables that tap into them. To make the discussion more concrete, we start by giving a brief overview of the data sources available to operationalize the learning antecedents.

Data

We aim to include a number of learning drivers as independent variables in the second stage model. To operationalize these drivers, we access information from three data sources: the scanner data and two surveys. The first survey is administered to the panel members by GfK. This survey records *households'* scores on a number of items related to their shopping behavior, and can be linked with the panel members' individual purchase histories. The second survey, by contrast, is administered[3] to Dutch consumers who are not members of the panel, and yields summary measures on a number of *category* characteristics that do not vary across households or over time. Table 2.4 presents descriptive statistics of the variables (please see Table 2.5 for detailed variable operationalizations).

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[3] These data were collected in the context of a "Global Private Label" study by AIMARK. We thank Inge Geyskens and Jan-Benedict Steenkamp for making part of the information available to us for this research.

TABLE 2.4 DESCRIPTIVE STATISTICS OF VARIABLES IN SECOND STAGE MODEL

	Mean	Std. Deviation
Logarithm of consumption signal variance	-.6368	4.21286
Purchase Frequency	.2510	.27151
Category expensiveness	.0787	.87205
Performance Risk	2.3344	1.15421
Number of different brands consumed	.5646	1.06570
Brand loyalty	2.1660	1.64296
Need for variety	2.3066	1.19231
Dummy for food categories	.6298	.48298
Mavenism	4.9464	3.24183
Purchase planning	2.2601	1.81388
Consumption weeks per unit	1.7846	.47442

Drivers of consumption-based learning

Level of Uncertainty. We expect learning from consumption to be lower, and our learning parameter to be higher, for consumers and categories where there is less quality uncertainty. When a consumer's knowledge of a given category is more developed, each consumption experience provides relatively less new information and, hence, there is less learning taking place.[4] This expectation is in line with findings that more experienced consumers have more stable preferences as they have identified brands that maximize their utility (Heilman et al. 2000). It is also in line with studies of consumer learning from sources other than consumption, which show that consumers who are more uncertain learn more. For

[4] As pointed out above, our learning parameter captures the weight attached to the new consumption signal vs. the consumer's prior quality beliefs: the lower the uncertainty of the prior beliefs, the less learning from the new consumption experience.

instance, Ackerberg (2001) shows that inexperienced consumers learn more from informative advertising than non-experienced consumers, while Pechmann and Ratneshwar (1992) find that consumers, when lacking information, infer quality from price.

We measure the level of accumulated consumer knowledge by the household's '*purchase frequency*,' i.e., the average number of category purchases per week, and hypothesize its impact on learning magnitude (the consumption signal variance) to be negative (positive).

Incentives to learn. We expect consumer learning to be positively related to the anticipated gains from learning. This claim stems from the focal notion in information economics that searching for information comes at a cost, which is justified if consumers expect to obtain sufficient gains (Stigler 1961). Greater gains from learning may incite consumers to pay more attention to the actual performance of a brand, and greater involvement can lead to stronger learning (Hawkins and Hoch 1992).

We have two indicators of consumers' incentives to learn, one related to monetary, and another to non-monetary, gains from learning. First, we expect consumers to have higher stakes in learning about brands in categories where the expenses incurred on a single (brand) purchase are sizable. Differently stated: products that require a high discretionary sum spent on a single purchase occasion are likely to motivate consumers to learn. We quantify this, '*category expensiveness*,' as the category- and household-specific average price paid by the household per average purchase volume in the category, relative to other sample categories, and we expect it to be positively associated with learning magnitude (or negatively with the learning parameter). Second, incentives to learn may be related to the '*performance risk*' inherent in the category, that is, the loss the consumer expects to experience in case of a wrong brand choice in the category. The greater the performance risk in a given category, the stronger households will be motivated to learn from experience, in order to avoid mistakes. We capture this notion through the category-specific score from the survey.

TABLE 2.5 OVERVIEW OF INDEPENDENT VARIABLES

Underlying dimension	Variable name	Expected effect on learning parameter	Variable origin	Source of variation	Operationalization
Level of uncertainty	Purchase frequency	+	Scanner data	Households and categories	Households' average number of purchases per week in a category
Incentives to learn	Category expensiveness	-	Scanner data	Households and categories	Average price per unit paid by the household in a category, relative to other categories
Incentives to learn	Performance risk	-	Non-panel-member survey	Categories	Score average for the following items:5 - There is much to lose if you make the wrong choice in category X - It matters a lot when you make the wrong choice in category X - In category X, there are large differences in quality between the various products
Variety seeking	Number of brands consumed	+	Scanner data	Households and categories	Number of brands bought by the household in a category
Variety seeking	Brand loyalty	+	Panel-member survey	Households	Score average for the following items:5 - I will pay more for a better quality product - I consider myself a brand-loyal consumer - I really feel connected with brands that I buy
Variety seeking	Need for variety	+	Non-panel-member survey	Categories	In category X, I want a large variety of products to choose from5
Control variable	Dummy for food categories	+/-	Scanner data	Households and categories	Dummy equal to 1 for food categories and to 0 for non-food categories
Control variable	Mavenism	+/-	Panel-member survey	Households	Score average for the following items:5 - I talk with friends about products I buy - Friends and neighbors often ask me for advice - People often ask me what I think about new products
Control variable	Purchase planning	+/-	Panel-member survey	Households	Score average for the following items:5 - When I go shopping I know exactly what I want to buy - I plan my purchases carefully so that supermarket visits will cost less time - I make a list before I go shopping and stick to it
Control variable	Consumption weeks	-	Scanner data	Categories	Average volume per purchase/average volume consumed per week

[5] The instrument uses a five-point scale (1 = strongly disagree; 2 = disagree; 3 = agree nor disagree; 4 = agree; 5 = strongly agree).

Variety seeking. Variety seeking is the third dimension we associate with the magnitude of consumption-based learning. Variety seeking and learning are associated with different underlying processes and patterns of behavior. While learning is driven by the desire to maximize the expected quality of brands consumed, variety seeking is associated with the desire to mitigate boredom and satiation (Gijsbrechts et al. 2000; McAlister and Pessemier 1982). Previous research has documented that consumers with an intrinsic desire for variety in a given category may be willing to give up quality in return for variety (Kahn and Raju 1991; Trivedi and Morgan 2003). Therefore, we expect variety seeking consumers to take less interest in learning about the quality of specific brands and hence learn less. We adopt three indicators of variety seeking. Our first measure is the 'number of different brands purchased' by a household in a given category, which we expect to reduce the amount of learning (increase the learning parameter). While this behavioral measure has the advantage of being both household- and category-specific, it does not directly tap into the consumers' intrinsic need for variation (but may, for instance, reflect deal proneness or exploratory behavior). Our second indicator is a consumer characteristic obtained from the panel-member survey data, and reflects the panel member's typical degree of 'brand loyalty,' or commitment to his/her favorite brand in different categories. We expect low values of this variable to indicate high variety seeking and, hence, weak learning. The third variable is a category-specific, survey-based measure that quantifies the 'typical need for variety in the category.' We expect higher values for this variable to be associated with less learning (and higher learning parameters).

Control variables. Apart from these hypothesized drivers, we include several control variables. First, we incorporate a *dummy variable for food categories* to distinguish them from non-food categories. Next, we include two household characteristics, obtained as summated scales from the panel-member survey. One of these variables, *mavenism*, reflects the extent to which the consumer acts as an opinion leader and shares his/her product information and experience with other consumers. The other variable captures the consumer's degree of *purchase planning* through, for instance, use of a shopping list. As we expect shopping mavens or planned buyers to be more involved grocery shoppers (who are more eager to learn), but also more knowledgeable shoppers (who have little left to learn), we offer no directional hypotheses on their degree of consumption-based learning. Finally, as indicated in Section 2, our estimated learning parameter reflects the amount of information (or lack thereof) in one ‘unit’ where a ‘unit’ is resized in each category to reflect average purchase volume. Yet, these consumption units may represent higher ‘numbers’ of consumption experiences in some categories – for instance, in easily storable, non-perishable categories – than in others. For instance, the average purchase volume for coffee may be one 250gr package, and the average household may consume one such pack per week. For liquid detergents, the average purchase volume may be a one liter bottle, and the average household may use up one such bottle every month. To accommodate this, we introduce the variable *consumption weeks per unit*, which is defined as the average purchase volume divided by the average weekly consumption rate in the category across households. Hence, it captures the number of weeks a typical consumer will get by after adopting the volume equivalent of one unit. For instance, in our coffee example, the variable ‘consumption weeks per unit’ would equal 0ne, and for liquid detergents it would equal four. We expect the effect of this variable on the learning parameter to be negative, with consumers learning more from packs that cover more consumption-weeks.

Table 2.5 provides an overview of the learning drivers included in the second stage model, together with the underlying dimensions, and their operationalizations.

2.3.2 Method

As indicated above, the second stage of analysis uses the posterior learning parameters across households and categories as dependent variables in an exploratory model with the category- and household-related learning antecedents as independent variables. Given that the dependent variable (variance of the consumption signal) is constrained to be positive, we adopt a log-linear specification in the regression model (except for the explanatory variable *consumption weeks per unit*, which also enters in log form for reasons specified below). In fact, the logarithm of the learning parameter, our dependent variable in the second stage regression, is the value that was estimated in the first stage equation.

We employ a hierarchical linear model (HLM) to account for the fact that our data includes two, naturally distinguishable levels:

$$\bar{\sigma}_{gci}^{2} = B_1 * Dr_{1i} + B_2 * Dr_{2c} + B_3 * Dr_{3ic} + w_{1i} + w_{2ci} \qquad [2.6]$$

In this expression, $\bar{\sigma}_{gci}^{2}$ is the posterior estimate of the learning parameter for household i and category c, based on the stage 1 analysis. B_1, B_2, and B_3 are parameter vectors capturing the sensitivity of this learning parameter to the variables in matrices Dr_1, Dr_2, and Dr_3 , which are household-, category-, or household and category specific. w_1 is a household-specific error term such that $w_1 \sim N(0,\delta_{w1})$, and w_2 is a household- and category-specific error.

Since our dependent variable is a posterior of an estimated parameter, with an associated sampling error that may vary across observations and, this calls for the use of weighting. To assess the sampling error, we compute for each category and household a range of posterior values of the learning parameter, using sets of parameters drawn from the multivariate normal/log-normal mixing distribution obtained from the Bayesian learning models. We then compute, for each category and household, the standard deviation of the resulting posteriors of the learning parameter. In each case, the sampling error turns out to be very small, rendering weighting superfluous.

The second source of potential heteroskedasticity stems from cross-category differences in the error variance in the second-stage regression. To accommodate this, we first run the model described in equation [2.6] using maximum likelihood, and then use the estimated error variances by category to construct the weights (i.e., we use the inverse of the standard deviation of the model [2.6] error term within categories for a second-round weighted-HLM.

2.3.3 Results

Table 2.6 reports the results of the second stage regression. With an adjusted R^2 of 33.8 %, the model fit is quite good and, taken together, the learning drivers explain a significant portion of the learning parameter variation (p<.00). The variance inflation factors in our model all remain below 6, indicating that we do not have severe collinearity problems.

For interpretation of the results it is important to recall that our dependent variable is a posterior of the learning parameter (i.e., the consumption signal variance), and that the lower this parameter, the more learning takes place. Thus, variables associated with negative coefficients will imply less variance in the consumption signal and more learning. In order to facilitate the comparison of the effects across variables, we focus on standardized coefficients.

The results support our expectation that consumer learning is associated with incentives to learn and variety seeking. More specifically, as expected, we find that learning is higher (β=-.418, p<.01) in categories characterized by high performance risk: consumers are reducing their level of uncertainty by closely monitoring their consumption experiences in these categories. In line with expectations, consumption-based learning is stronger in expensive categories (β= -.086, p<.05) where, again, the stakes for consumers are expected to be higher. Further, as anticipated, variety seeking tends to reduce the degree of experience-based quality updating: the learning parameter is significantly higher in categories with a high need for variety (β=.571, p<.01) and in which the consumer buys many different brands (β=.107, p<.01). The consumers' general tendency to be brand loyal, however, proves insignificant. In all, these findings are in line with previous results that category-specific variety seeking, rather than variety seeking in general, is a good predictor of consumers' behavior (Campo 1997).

Surprisingly, contrary to our expectations, consumers update their consumption quality beliefs more strongly (β= -1.647, p<.01) if they frequently purchase from a category. In hindsight, the underlying explanation may be that *purchase frequency* reflects consumers' stakes in the category (i.e., their incentives to learn) rather than their level of knowledge. It seems that purchase frequency motivates consumers, despite any extensive category experience, to closely keep track of the brand's performance.

As for the control variables, we find significantly more learning in food categories (β=-1.211, p<.01). We also find that consumers who act as shopping mavens, or plan their purchases in advance, are no different from others in their consumption-based learning (β=-.000, p=.987 and β=.003, p=.890, respectively). In contrast, we find a strong and significant effect for the number of consumption weeks covered by a typical purchase unit (β=-3.185, p<.01). It is interesting to note that the unstandardized coefficient of this variable is significantly below -1. Given that both the dependent variable and this explanatory variable are log transformed, it follows that the information content in a 'consumption unit' (i.e., the average quantity bought per occasion) increases disproportionately as the consumption unit covers longer consumption periods. (A coefficient of -1 would imply that a 1% increase in the number of consumption weeks covered by a consumption unit would lead to a same-size (1%) decrease in the consumption signal variance. With a coefficient below -1, we find the decrease to be stronger.) This, again, seems consistent with the finding that consumers monitor their consumption experiences more closely for consequential purchases.

TABLE 2.6 SECOND STAGE RESULTS

Variable	Unstandardized coefficients	Standardized coefficients	p-value
Constant	3.3847	9.848	0.000
Purchase frequency	-0.3678	-1.647	0.001
Category expensiveness	-0.0557	-0.086	0.043
Performance risk	-0.4946	-0.418	0.000
Number of different brands consumed	0.0884	0.107	0.000
Brand loyalty	-0.0028	-0.002	0.930
Need for variety	0.6616	0.571	0.000
Dummy for food categories	-0.5198	-1.211	0.000
Mavenism	-0.0003	0.000	0.987
Purchase planning	0.0033	0.002	0.890
Consumption weeks per unit	-1.7597	-3.185	0.000

Note: Dependent Variable: 3 log of learning parameter (consumption signal variance), weighted HLM

2.4 Discussion, limitations and future research

Recent empirical findings have already suggested that consumption-based quality learning not only occurs in infrequently purchased, high involvement or strongly evolving categories, but also prevails for consumer packaged goods. However, the findings to date were restricted to only a few categories, which begged the question of generalizability. In this study, we assess the prevalence of consumer learning across a set of 20 packaged goods categories. Moreover, we study the co-variation of households' learning magnitude across these categories, and investigate household and category characteristics that drive learning.

Findings. Our main findings are as follows.

First, we find some evidence of learning in almost all of the categories: for each of the considered products, consumers are found to update their beliefs about brand quality based on their consumption experiences, and this leads to a significant improvement in fit in 18 out of 20 cases. At the same time, the degree of learning does vary substantially across products. For instance, we find that after a first consumption experience, households range from basing their quality beliefs entirely on the initial consumption signal in some categories (e.g., dish detergents) to updating less than 10% of their quality beliefs in others (e.g., rice and pasta). In some categories, learning is really minimal. This is, for instance, the case for toilet and kitchen tissue, where only 4.2% of the brand's quality is influenced by the initial purchase.

Second, we find that households vary in their degree of consumption-based learning; the across-category variation is more than twice greater than across-household within-category variation. Interestingly, we observe very low (absolute) correlations in households' learning across categories, and the pair-wise correlations are as often negative as they are positive. This suggests that consumption-based knowledge updating is not predominantly a household trait, and that households that are strong learners in some categories may be weak learners in others.

Third, our results reveal that both household- and category-related characteristics significantly affect the degree of consumption-based learning. As expected, consumers attach more weight to experienced consumption quality in categories with high performance risk.

Furthermore, they update their quality beliefs more strongly in categories that they purchase frequently, and for products where a typical purchase is expensive and/or lasts for several consumption weeks. Higher ‘stakes’ in these categories mean that households have extra incentive to learn. Conversely, the need for variation and the tendency to buy multiple brands detract from consumption-based updating.

Managerial implications. Our findings have several implications for managers. First, since learning does prevail in many packaged goods, investment in product quality is likely to have an impact on brand choice that builds up gradually over subsequent consumption occasions. Conversely, quality deterioration is expected to be particularly detrimental in these same categories and brands. The size of the impact (both the immediate effect and the impact after several consumption occasions) varies across categories. Our results suggest that investments in product improvements are more likely to pay off in categories that are expensive, that are perceived to have high performance risk, and where variety seeking and satiation is not much of an issue.

Second, the finding suggesting that the learning magnitude is not a household trait and that consumers differ in their degree of learning within categories, may be relevant to managers. The low cross-category correlations in learning magnitude may pose a challenge for brand extensions: consumers who learned about the original brand may fail to update their quality beliefs in the extension category. Moreover, consumer heterogeneity suggests that managers may wish to target their quality improvements to households that learn well. Since positive consumption experiences are especially impactful with frequent category buyers and consumers who do not seek variety, managers should focus quality monitoring and investment on product versions preferred by these consumers – for example, ‘mainstream’ flavors or varieties, like strawberry jam or regular tea. These products should have upscale positioning and come in larger packs, unlike the small-sized fringe varieties, like raspberry-coconut tea. Also, our results seem to imply that true quality improvements do not automatically and equally present themselves to all product users. In all categories we observe consumers who do not learn, and marketers need to find ways to reach both learning and non-learning consumers. For instance, non-learners (e.g., variety seekers, bargain seekers, or small pack buyers) might benefit from extra communications support in order to appreciate true quality changes.

Limitations and future research

Our study suffers from a number of limitations that open up interesting opportunities for future research. First, the inclusion of more products would allow exploration of additional category characteristics of learning – something we could not comfortably achieve with 20 categories under study. Second, the inclusion of more brands than just the top three brands should increase the generalizablity of the findings. It could also lead us to discover stronger learning, as top brands are likely to be better known to consumers than less popular brands, and, therefore, subject to weaker learning. In that sense, we expect our analysis to provide a conservative estimate of the degree of learning – something to be verified in future studies. Third, even though our model results are significant, they still leave a sizable portion of variation unexplained, especially household-category-related variation. Extending the list of learning drivers by perceptual and attitudinal variables could further improve our ability to explain when and why households learn from consumption. Our findings of low cross-category correlation in learning magnitude suggest that variables that are both household- and category-specific, or interactions of category-specific and household-specific variables, are most promising in explaining magnitude of consumer learning.

On the methodological side, we imposed the distribution of the learning parameter in each category to be log-normal. Testing alternative formulations could result in more precise estimates of the learning parameter. Additionally, simultaneous estimation of the category-specific Bayesian learning models, in which the learning parameter is a function of learning drivers, could yield more efficient estimates (Ainslie and Rossi 1998). From a broader perspective, our measure of learning – as is the case in previous choice models with Bayesian updating – is an implicit one, since brand quality beliefs are latent and unobserved. Future research could replicate our study of learning drivers in packaged goods using alternative, more direct ways of assessing consumer learning and knowledge, for example, laboratory or natural experiments and surveys. Also, a challenge in our type of learning models for frequently purchased goods is that we seldom observe the start of the consumption history, which renders estimation of the initial quality beliefs and variances non-trivial. Moreover, we do not observe consumers' purchases in all stores where they can purchase the sample brands, which may bias the learning parameter estimate. A small simulation exercise indicates that the magnitude of the bias is related with the share of the household's brand purchases observed: the greater the share of observed purchases, the smaller the upward bias. The bias is also greater if unobserved brand purchases take place early in the consumer's purchase history, a problem largely mitigated by our use of an initialization period. Studies focusing on new markets, and new consumers to a market, could facilitate the development and assessment of methods for estimating prior quality beliefs and the learning magnitude.

Finally, our analysis focused on brand learning only within categories. Analyzing whether and how consumers update their beliefs about umbrella brands, across categories, is a challenging topic for future study.

3 Conditional Cross-Brand Learning: When Are Private Labels Really Private?

3.1 Introduction

The growth of retailer-owned or private label (PL) brands represents one of the most notable trends in marketing in recent decades. Private labels constitute 17% of the sales value of fast moving consumer goods worldwide, including 16% in the United States (AC Nielsen 2005) and more than twice this figure in some European countries (e.g., 39.6% in the United Kingdom, 46% in Switzerland; Planet Retail 2007 p.7). Accordingly, academic marketing literature pays close attention to this issue (Ailawadi 2001; Hansen et al. 2006; Hoch 1996; Steenkamp and Dekimpe 1997), but whereas most PL research relates to competition between PLs and national brands (NBs) (Cotterill et al. 2000; Du et al. 2005), PLs also may represent key elements in the context of retail competition (Ailawadi et al. 2008; Hansen and Singh 2008).

Extant research on the latter topic suggests that investments in PL can increase chain differentiation and loyalty (e.g., Corstjens and Lal 2000) for three reasons. First, unlike NBs, PLs are often the only chain-exclusive brands offered. Second, retailers have a direct impact on quality positioning, such that PL investments can differentiate the retailer brand and create brand loyalty. Third, because retailer brands are chain-specific, brand loyalty initiates chain loyalty. Both academics (Corstjens and Lal 2000; Marketing News 1987) and leading retail practitioners adopt this line of reasoning; as Ahold's CEO Anders Moberg (2006) claims, "With private labels, we can better differentiate ourselves and our brands. We can increase customer loyalty." Thus, retailers' investments in PL quality positioning should be valuable because they set them apart from the competition.

However, this reasoning assumes that consumers distinguish among different PL brands and that PL investments allow the retailer to set its PL brand apart favorably. Yet several indications imply that consumers perceive PLs as homogenous or similar across retailers (Ailawadi 2001). In an experimental setting, Richardson (1997 p. 393-394) finds that "consumers perceive no differentiation between the … store brands." Research on consumer PL proneness further indicates that both researchers and consumers consider PLs as a group of similar brands that share common demand drivers across chains (Ailawadi 2001; Bonfrer and Chintagunta 2004; Burger and Schott 1972), classified within a single mental "PL brand" category (Ailawadi and Keller 2004). Thus, a retailer's PL investment may not exclusively enhance the appeal of its own brand and chain but also may benefit competing PLs.

In sum, literature to date leaves compelling questions unresolved: Do investments in PL quality positioning increase retailer differentiation or benefit the reputation of all PLs? If all PLs benefit from investments of one retailer, is this result good or bad for retailers? The core underlying issue entails the extent to which consumers differentiate among retailers' PLs or, conversely, use information about one PL to learn about another, as well as how product quality positioning may influence this belief. Our study addresses this issue through the following research questions:

RQ1: Do consumers generalize their knowledge across PL brands, by learning from their consumption of one PL brand about the quality of other PL brands?

RQ2: What boundary conditions affect cross-brand learning; is it equally strong for all pairs of PL brands, regardless of their quality positioning?

RQ3: What are the implications of cross-brand learning for PL brands with different quality positioning levels?

We study these questions in a context in which risk-avoiding consumers patronize multiple chains that offer both NBs and PLs. Consumers choose brands from a product category in a store on the basis of quality, but they are uncertain about brand quality, and must seek information from available sources. In such a setting, cross-brand learning among PL brands (RQ1) has important implications for retail chains, because it would reduce their potential to differentiate on the basis of their PL offer. If consumers engage in cross-brand learning, does their learning always occur and to the same extent , or does it exist only if consumers have limited experience with specific PL brands? Finally, even if these effects occur, can a PL break away (or be expelled) from the mental category (RQ2)? The answers to these questions are important for PL quality positioning (RQ3). As quality belief spillovers become more prevalent, a high-quality positioning should become less appealing, in the sense that a high-quality PL would subsidize other PLs while suffering from their low-quality reputation. Yet, for both high- and low-quality PLs, consumption of PLs should make customers more familiar with the retailer's own PL and hence reduce perceived purchase risks.

To investigate these issues, we develop a structural brand choice model that features consumer learning about brands' quality, based on their consumption experiences with the brand and with other brands in the same mental category (i.e., PL brands). The dependent variable is brand choice, given chain choice and category purchase incidence. Our model thus extends models by Erdem and Keane (1996), Mehta, Rajiv, and Srinivasan (2004) and Narayanan, Manchanda, and Chintagunta (2005) by including cross-brand learning among PLs and making this cross-brand learning contingent on both PLs' specific quality positioning and the precision of consumers' knowledge about brand quality. We calibrate the model with a scanner panel data set of purchases in the liquid dish detergent category over 130 weeks and across nine retail chains, five of which have their own PL brands.

The remainder of this chapter consists of three main parts. First, we develop our conceptual framework. Second, we specify a model that captures this process and elaborate on the empirical analysis and estimation results. Third, we present a series of simulations that shed more light on the implications of cross-brand learning for PL brands with different quality positions. We conclude with some limitations and suggestions for further research.

3.2 Conceptual Framework: Quality learning across Private Label brands

Our framework is rooted in literature that recognizes consumers have imperfect knowledge about product quality and base their brand choice) decisions on perceived rather than true quality (e.g. Steenkamp 1990; Zeithaml 1988). Such quality beliefs build over time as consumers learn about brands' quality from, e.g., consumption, advertising, and prices (Erdem et al. 2008). Prior consumption of the product provides information for updating quality beliefs, but in some instances, the consumption of other products that belong to the same mental category can also offer signals of the focal product's quality and thus enable consumers to update their beliefs and reduce uncertainty. We argue that PLs constitute a mental category, within which such cross-signaling, or cross-learning, takes place; we further investigate the degree of cross-learning within this mental category.

3.2.1 Private Label Brands as a Mental Category

According to categorization theory, people group objects that share known properties into categories to facilitate predictions of their unknown properties on the basis of their category membership (Anderson 1991). This categorization framework is, for instance, widely applied in marketing to conceptualize 'umbrella brands' that span multiple products as mental categories (e.g., Meyvis and Janiszewski 2004). Various studies show that consumers evaluate new brand extensions according to their beliefs about the umbrella brand (e.g. Erdem and Sun 2002; Swaminathan et al. 2001). Moreover, people update their beliefs about category members to maximize the category's predictive validity (Anderson 1991). Evidence on such feedback or reciprocal effects emerges from research into brand extensions, which finds that consumers update their beliefs about a parent brand after experience with extensions of that brand (e.g. Balachander and Ghose 2003; Loken and John 1993; Swaminathan et al. 2001).

In turn, we contend that consumers may view PL brands as a mental category (separate from NBs), within which information spillovers are likely. Mental categories are formed for predictive purposes: categorization is based on a known attribute so the person can predict some other, unknown attribute (Anderson 1991). To be useful as a basis for categorization, an attribute must meet two criteria: It must be observable by the consumer, and the consumer must believe it is a valid predictor of unknown attribute. The PL brand attribute meets both criteria. First, in most cases, consumers can easily identify PL brands. Retailers explicitly promote PLs as their own, and PLs often carry the name of the retailer (e.g., Tesco, Ahold). Moreover, PLs typically span a much wider range of product categories than do NBs (Hoch 1996), which provides an additional signal that a given brand is a PL.

Second, as Ailawadi (2001) notes, most PLs lack objective (physical) forms of differentiation. Retailers procure PLs from manufacturers of undifferentiated goods so that they may pay lower wholesale prices, whereas NB manufacturers hope to increase differentiation among brands, decrease price competition, and obtain higher margins. Therefore, PLs likely are relatively homogenous in terms of objective quality, whereas NBs are not. More importantly, extensive literature on consumer PL proneness (Ailawadi 2001; Bonfrer and Chintagunta 2004; Burger and Schott 1972) and consumer brand choice (Baltas et al. 1997) also suggests that consumers perceive PLs as relatively homogeneous and different from NBs. The consumer characteristics that suggest they will purchase PLs remain homogenous across chains (Ailawadi, Neslin, and Gedenk 2001; Bonfrer and Chintagunta 2004). Also, PL buyers hold different beliefs about retail brands' quality (Ailawadi et al. 2003b; Narasimhan and Wilcox 1998) and risk (Batra and Sinha 2000) compared with NBs. On the basis of an extensive survey, Richardson, Jain, and Dick (1996) conclude that consumers maintain separate quality associations for each brand type, and Richardson (1997) finds in a field experiment that consumers perceive PLs of different retailers to have uniform quality. This evidence suggests that consumers perceive PLs as a homogenous category, different from NBs.[6] Therefore, PL brands should constitute a separate mental category that is diagnostic for brand quality evaluation and that leads to possible spillovers of consumption

[6] We do not predict the *sign* of the perceived correlation between PL category membership and quality—whether PLs or NBs are believed to be better—but rather consider only whether consumers view the quality of PL brands as similar.

signals across category members. Therefore, we expect consumers to use their consumption experience with a PL brand to update their quality beliefs of other PL brands.

3.2.2 Strength of Cross-Brand Learning Among Private Labels

Mental categorization theory suggests that consumers do not use categories as unconditional predictors; rather, information spillovers between objects in a category depend on their attribute similarity (Anderson 1991), so atypical objects may be excluded from the category (Gurhan-Canli and Maheswaran 1998; McCloskey and Glucksberg 1978). Research on brand extensions, for instance, shows that beliefs about parent brands are less likely to generalize to atypical extensions (Aaker and Keller 1990; Boush et al. 1987) and, conversely, that atypical extensions have a less predominant influence on beliefs about the parent brand (Loken and John 1993).

Such effects also seem likely for quality learning among PL brands. We contend that the extent to which consumers use a consumption experience with one PL brand to adjust their quality beliefs of another PL brand depends on their (current) assessment of these brands' similarity. Specifically, when quality differences between specific PL brands are larger or become more apparent (e.g., because of consumers' more precise consumption-based knowledge), quality spillovers among brands should diminish.

Our expectations thus imply that PLs represent a homogenous group of products and that consumers use information obtained through their consumption of any PL brand to build their knowledge about other PLs and, hence, for the entire PL category. However, over time, as consumers develop their knowledge about brands' quality, they may grow convinced that specific PLs have different quality positions and therefore decide to build their knowledge about these brands independently, that is, with weaker cross-brand learning.

These expected processes have key implications for PL brands. In particular, cross-brand learning would lead to reputation spillovers, in which knowledge based on one PL spills over to others. If the strength of cross-brand learning depends on perceived similarity, as we argue in H_2, so will the magnitude of reputation spillovers. We next develop and estimate a model that captures cross-brand learning, and then use simulations to gauge the magnitude of reputation spillovers and illustrate the implications for PL brands with different quality positions.

3.3 Model Development

The brand choice model we develop enables us to verify our expectations. The model builds on existing structural dynamic choice models with consumer brand quality learning and forgetting (Erdem and Keane 1996; Mehta et al. 2004; Narayanan et al. 2005) but extends them by including cross-brand learning (i.e., consumption of one brand leads to updated beliefs about other brand(s) among PL brands. Moreover, we allow the extent of cross-brand learning to depend on consumers' perceived brand-pair similarity, which itself depends on the PL's specific quality positioning and consumers' uncertainty about brands' quality. Note that the development of the model without cross brand learning in sections 3.3.1 and 3.3.2 is completely similar to that in the previous chapter.

3.3.1 Utility in the Presence of Brand Quality Uncertainty and Risk Aversion

We assume that when choosing from a category assortment, consumers pick the brand that maximizes their (current) utility, which depends on brand quality. We allow the "true brand quality"[7] to be heterogeneous across consumers and assume that true brand quality is not perfectly known, so consumers' choices on different purchase occasions rely on their quality beliefs of different brands at that time. Moreover, in line with prior findings (e.g., Erdem and Keane 1996), we assume that consumers are risk averse with respect to their uncertainty about the true quality of brands.

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[7] Similar to previous studies (e.g., Erdem and Keane 1996), we assume brands have a "true quality" that consumers could know if they had perfect knowledge about the brand. Following more recent work (e.g.,Erdem, Sun, and Keane 2008; Narayanan, Chintagunta, and Manchanda 2005), we allow this quality evaluation with perfect knowledge to differ across consumers.

Specifically, we derive the following expression for the utility of brand j on purchase occasion t:[8]

$$U_{jt} = f(Q_{jt}) + X_{jt}\beta + \varepsilon_{jt}\,, \qquad [3.1]$$

where Q_{jt} indicates the consumer's quality beliefs about brand j on purchase occasion t, X_{jt} represents a vector of utility determinants other than perceived quality observed by both the researcher and the consumer, β are parameters capturing sensitivity to those determinants, and ε_{jt} are i.i.d. extreme value distributed portions of utility unobserved by the researcher but observed by the consumer (for an extensive discussion, see Mehta, Rajiv, and Srinivasan 2004).

The specification of $f(Q_{jt})$ reflects our specific assumptions about consumers' risk aversion. A linear function implies risk neutrality, whereas a nonlinear specification implies that consumers are not risk neutral. Like previous studies (e.g. Crawford and Shum 2005; Narayanan and Manchanda 2009), we assume constant absolute risk aversion, which implies that the disutility of a certain level of quality uncertainty is the same for brands with different quality levels – an appropriate assumption in the absence of dramatic quality differences across brands. We capture this aversion by specifying f as a negative exponential function:

$$f(Q_{jt}) = -\exp(-rQ_{jt})\,, \qquad [3.2]$$

where r is a risk aversion coefficient that is greater than 0.

Moreover, the consumers' quality belief of brand j on purchase occasion t, Q_{jt}, follows a normal distribution:

$$Q_{jt} \sim N(\mu_{jt}, \sigma^2_{jt})\,, \qquad [3.3]$$

[8] We drop the subscript for consumer for clarity of exposition.

where μ_{jt} is the mean quality belief on purchase occasion t, and σ_{jt}^2 the quality belief variance (or uncertainty). Because consumers do not know the brands' true quality q_j but instead assess utility on the basis of their quality beliefs at purchase occasion t Q_{jt}, this utility is stochastic from the consumer's perspective.[9] Therefore, the consumer maximizes his or her expected utility, given by:

$$E[U_{jt} \mid I_t] = E[f(Q_{jt}) \mid I_t] + X_{jt}\beta + \varepsilon_{jt}, \qquad [3.4]$$

where I_t indicates the information set the consumer possesses on purchase occasion t. By inserting Equations [3.2] and [3.3] into Equation [3.4], we can write the expected utility of brand j on purchase occasion t as (Crawford and Shum 2005; Narayanan and Manchanda 2009):

$$E[U_{jt} \mid I_t] = -\exp\left(-r\left(\mu_{jt} - r\frac{\sigma_{jt}^2}{2}\right)\right) + X_{jt}\beta + \varepsilon_{jt}. \qquad [3.5]$$

3.3.2 Quality Learning and Forgetting Based on Consumption

Similar to previous learning models, we assume that though consumers do not know brands' true quality, they learn about it from their consumption. Consumers update their brand quality beliefs as if they were Bayesian learners, and each consumption episode provides a noisy signal about the true underlying brand quality. The noise in consumption experience results from inherent product variability (Roberts and Urban 1988) or the consumer's misjudgment of the quality of a brand based on a particular consumption experience.

[9] Note that ε_{jt} is known to the consumer and therefore not stochastic from the consumer's perspective.

However, even though these consumption signals allow consumers to learn about quality, they also forget them over time.

We model this process of learning and forgetting as follows: The decay in consumers' brand knowledge over time entails increases in consumers' uncertainty about brand quality (i.e., increase in σ_{jt}^2). In the absence of consumption at t – 1, we expect σ_{jt}^2 to decay exponentially, $\sigma_{jt}^2 = \sigma_{jt-1}^2 * e^{b(w_t - w_{t-1})}$, where b is the decay parameter, and $w_t - w_{t-1}$ refers to the time elapsed between purchase occasions t and t – 1. This process of uncertainty increase due to forgetting is similar to that described by Mehta, Rajiv, and Srinivasan (2004).

If however, the consumer buys and consumes M_t units of brand j in period t – 1, each unit m of the product (e.g., ounce) provides a (new) quality level experience, which we refer to as a consumption signal g_{jtm}. We assume this signal is i.i.d. normally distributed with a mean equal to the true brand quality q_j and variance σ_g^2, such that $g_{jtm} \sim N(q_j, \sigma_g^2)$. The consumer's quality belief of brand j from purchase occasion t – 1, Q_{jt-1}, then gets updated in a Bayesian manner with the consumption signal g_{jtm}. At time t, the consumer updates prior quality beliefs with a series of M_t consumption signals. We summarize this series of unobserved signals g_{jtm} with a mean G_{jt}, which is also i.i.d. normally distributed, $G_{jt} = \frac{\sum_{m=1}^{M_t} g_{jtm}}{M_t} \sim N\left(q_j, \frac{\sigma_g^2}{M_t}\right)$. Because both prior beliefs about brand quality and consumption signals follow a normal distribution, the resulting posterior belief will be normally distributed.

In line with previous studies , we assume that on each occasion t, the consumer adopts only one brand, such that $\sum_j d_{jt} = 1$, where $d_{jt} = 1$ if brand j were chosen at t and 0 otherwise. We also assume that consumption of the brand bought at t – 1 takes place right before the purchase in t, such that at the time of the update in t, the consumer has not forgotten the consumption signals g_{jtm}. Using the conventional expression for Bayesian mixing (e.g.Groot

1970), we derive the consumer's mean quality belief of brand j on purchase occasion t (μ_{jt}) and the variance of this quality belief (σ_{jt}^2) as follows:

$$\mu_{jt} = \left(\frac{\mu_{jt-1}}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \frac{d_{jt-1} G_{jt}}{\frac{\sigma_g^2}{M_t}} \right) * \left(\frac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \frac{d_{jt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1}, \qquad [3.6]$$

and

$$\sigma_{jt}^2 = \left(\frac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \frac{d_{jt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1}. \qquad [3.7]$$

3.3.3 Cross-Brand Learning Among Private Labels

In the model presented so far (which closely follows prior literature and builds on the previous chapter), consumers use the signal from the consumption of brand j, G_{jt}, to update their beliefs about brand j only. However, we expect that consumers may also classify different PL brands into a mental category and consider their experiences with one PL brand diagnostic for the others. Therefore, we extend the existing framework in two steps. First, we describe the model with complete cross-brand learning, in which cross-brand learning is not contingent on perceived brand similarity. Second, we introduce a model with contingent cross-brand learning.

Consider two brands, j and k, both belonging to the PL brand category. The consumer's quality belief of brand j gets updated with information obtained from his or her consumption of brand j and, because j is a PL brand, from his or her consumption of brand k. Given the standard assumptions that consumption signals are i.i.d. and that $\sum_j d_{jt} = 1$, the updating rule for the mean quality belief (μ_{jt}) of brands belonging to the PL brand type (denoted as the index set PL) becomes:

$$\mu_{\substack{jt \\ j\in PL}} = \left(\frac{\mu_{jt-1}}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \frac{\sum_{\substack{k=1 \\ k\in PL}}^{J} d_{kt-1} G_{kt}}{\frac{\sigma_g^2}{M_t}} \right) * \left(\frac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \frac{\sum_{\substack{k=1 \\ k\in PL}}^{J} d_{kt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1} . \qquad [3.8]$$

The variance of quality beliefs on purchase occasion t for a brand j of the PL category is

$$\sigma_{\substack{jt \\ j\in PL}}^2 = \left(\frac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \frac{\sum_{\substack{k=1 \\ k\in PL}}^{J} d_{kt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1} . \qquad [3.9]$$

Note that in this complete cross-brand learning model, updating for NBs (i.e., brand index $\notin$ PL) continues to take place according to Equations [3.6] and [3.7]. However, for any PL brand j, Equations [3.8] and [3.9] apply; when a PL brand k is consumed on purchase occasion t – 1 (d_{kt-1} = 1), quality beliefs of PL brand j are updated according to the consumption signals from brand k. When, however, the previously consumed product is a national brand, no quality updating takes place for brand j.

The cross-brand learning captured by Equations [3.8] and [3.9] implies the presence of reputation spillovers, which consist of two types: quality belief and familiarity. Quality belief spillovers, as captured by Equation [3.8], indicate that PL brands influence the mean quality beliefs of other PL products. Specifically, a poor quality PL brand receives an unduly high quality signal when people consume other, higher quality, PL products, whereas a high-quality PL may experience a downward adjustment of its mean quality beliefs because of consumption experiences with low-quality PL competitors. Equation [3.9] refers to familiarity spillovers, which occur because consumption of one PL brand reduces uncertainty about other brands in the PL brand category and, as a result of risk aversion, increases their expected utility. An important difference marks the two types of reputation spillovers: Whereas quality belief spillovers can lead to an increase or decrease in the expected utility of the receiving brands, familiarity spillovers always lead to utility improvements. Based on our estimation results, we will develop further simulations to illustrate the implications of these two types of reputation spillovers for PL brands with different quality positions.

3.3.4 Strength of Cross-Brand Learning Among Private Labels

The specification outlined above represents an extreme case that implies consumers consider their consumption of any PL equally diagnostic for the quality of all PL brands. However, consumers may be uncertain whether cross-signals are indeed diagnostic. Moreover, the beliefs of the degree of diagnosticity may vary across PL brand pairs and purchase occasions.

Therefore, we further extend the model described by Equations [3.8] and [3.9] by allowing consumers to update their beliefs of diagnosticity of the cross-signals and adjust their learning process. Specifically, the amount of cross-brand learning now depends on the consumer's belief that consumption of PL brand j provides an unbiased signal about the quality of another PL brand k. To this end, we introduce a weighting function P_{jkt} that reflects consumers' beliefs of the probability that g_{jtm} is an unbiased signal of the quality of brand k. The revised expression for μ_{jt} then becomes:

$$\mu_{jt} = \begin{cases} \left(\left(\dfrac{\mu_{jt-1}}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \dfrac{d_{jt-1} G_{jt}}{\frac{\sigma_g^2}{M_t}} \right) * \left(\dfrac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \dfrac{d_{jt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1} \right) & \text{if } \sum_{\substack{k=1 \\ k \in PL}}^{J} d_{kt-1} \neq 1 \text{ and/or if } j \notin PL \\ \sum_{\substack{k=1 \\ k \in PL}}^{J} d_{kt-1} \left(\begin{array}{l} (P_{jkt}) \left(\left(\dfrac{\mu_{jt-1}}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \dfrac{G_{kt}}{\frac{\sigma_g^2}{M_t}} \right) * \left(\dfrac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \dfrac{1}{\frac{\sigma_g^2}{M_t}} \right)^{-1} \right) \\ + (1 - P_{jkt}) \mu_{jt-1} \end{array} \right) & \text{if both } \sum_{\substack{k=1 \\ k \in PL}}^{J} d_{kt-1} = 1 \text{ and } j \in PL \end{cases} \quad [3.10]$$

Note that the top part of Equation [3.10] is valid when brand j is not a PL or if the consumer purchases a NB on the previous purchase occasion. In these cases, updating continues to take place as it would in a model without cross-brand learning. In all other situations, the bottom part of Equation [3.10] applies. This expression is a weighted average of Equations [3.6] (no cross-brand learning among PLs) and [3.8] (complete cross-brand learning among PLs).

The updated variance of brand j's quality belief in t therefore becomes (see Appendix 2):

$$\sigma_{jt}^2 = \begin{cases} \left(\dfrac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \dfrac{d_{jt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1} & \text{if } \sum_{\substack{k=1 \\ k \in PL}}^{J} d_{kt-1} \neq 1 \text{ and/or if } j \notin PL \\ \sum_{\substack{k=1 \\ k \in PL}}^{J} d_{kt-1} \left(\begin{array}{l} (2P_{jkt} - P_{jkt}^2) \left(\dfrac{1}{\sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}} + \dfrac{1}{\frac{\sigma_g^2}{M_t}} \right)^{-1} \\ + (1 - P_{jkt})^2 * \sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})} \end{array} \right) & \text{if both } \sum_{\substack{k=1 \\ k \in PL}}^{J} d_{kt-1} = 1 \text{ and } j \in PL \end{cases} \quad [3.11]$$

where the top part again applies when brand j is not a PL or a NB was last consumed, and the bottom expression is valid otherwise.

To specify the weights P_{jkt}, we consider the desirable properties of P_{jkt}, as follows: First, because P_{jkt} is a proportion, as indicated in Equation [3.10], it should fall in the range (0,1), where 0 represents the extreme case of no cross-brand learning and 1 is a situation of complete cross-brand learning. Second, in line with H_2, we postulate that P_{jkt} is a decreasing function of the difference between the mean quality beliefs of both brands $\mu_{jt} - \mu_{kt}$. The smaller the expected perceived quality differences between brands, the more consumers should consider their consumption signals mutually diagnostic. Third, we expect P_{jkt} to relate positively to the variances of quality beliefs of brand j and brand k, that is, σ^2_{jt} and σ^2_{kt}. The more imprecise the consumer's knowledge about brands' quality, the less able he or she is to tell brands apart and the higher his or her acceptance of a consumption experience with brand j as signal for the quality of brand k.

Keeping in mind these desirable characteristics, we adopt the following parsimonious expression for P_{jkt}:

$$P_{jkt} = \varphi * \left(2 * \left(1 - \Phi\left[\frac{\left| \mu_{jt-1} - \mu_{kt-1} \right|}{\sqrt{\sigma^2_{jt-1} + \sigma^2_{kt-1}}} \right] \right) \right)^{\kappa}, \qquad [3.12]$$

where j ∈ PL, k ∈ PL, Φ refers to the standard normal cumulative density function, and φ and κ are parameters to be estimated (which we call ceiling and contingency parameters, respectively) and $\left| \mu_{jt-1} - \mu_{kt-1} \right|$ is the absolute difference in mean quality beliefs for brand j and k at time t-1. We restrict them so that $\varphi \in (0,1)$ and $\kappa \geq 0$. For intuition, note that P_{jkt} can also be written as $\varphi * (1 - P^*_{jkt})^{\kappa}$, where P^*_{jkt} is the *p*-value in a test of true brand quality differences (H_0: $q_j = q_k$, H_0: $q_j \neq q_k$), given the information set on purchase occasion t. The lower P^*_{jkt}, the more likely the consumer is to reject the notion that brands j and k have the same quality, and the less likely he or she is to learn across PL brands. We assume the consumers construct P_{jkt} before updating beliefs about brand j. In short, our model implies that consumers assess the probability that the consumption signal is biased and adjust their degree of cross-brand learning accordingly.

Finally, the parameters φ and κ are crucial for our expected effects. The ceiling parameter φ captures the maximum probability of cross-brand learning, that is, the probability of cross-brand learning if the consumer believes brands j and k have identical quality level. For $\varphi \rightarrow 0$, P_{jkt} approaches 0 for all μ_j and μ_k, in which case the model reduces to that without cross-brand learning (i.e., Equations [3.6] and [3.7] instead of [3.10] and [3.11]). The contingency parameter κ captures whether and how the probability of cross-brand learning changes as a function of the perceived quality similarity of brands j and k. For $\kappa \rightarrow 0$, P_{jkt} approaches φ for all PL brands j and k at all t. In that case, cross-brand learning among PL brands is not contingent on perceived brand similarity. In contrast, an estimate of κ greater than 0 suggests that cross-brand learning is contingent.

3.3.5 Model Estimation

The estimation procedure closely resembles the one used in Chapter 2, the most important difference being that the data come from multiple chains, each with a potentially different variance for the Gumble-distributed error terms in the multinomial logit model. Below we elaborate in more detail on the estimation procedure.

Equations [3.5] and [3.10-3.12] complete the expected utility expressions for any household on purchase occasion t. Introducing i as a household indicator, we note that expected utility depends on a set of parameters $\Omega_i = \{q_{j,i}, \beta_i, \sigma_{g,i}, b_i, r_i, \varphi, \kappa, \sigma_0^2\}$ (for a notation overview, see Table A2.1 in Appendix 2); the covariates observed by the researcher and the consumer $X_{jt,i}$; the sequence of purchases by consumer i prior to purchase occasion t, $D_{t,i}=\{d_{jh,i}, h < t, j: 1, \ldots, J\}$; and a vector $\{E_{t,i}\}$ of sets of consumption signals $G_{jt,i}$ received by consumer i prior to purchase occasion t, which are observed by the consumer but not by the researcher.[10]

The dependent variable is household i's brand choice on purchase occasion t, given a chain choice and category purchase (summarized as $S_{t,i} = \{s_{ct,i}$, c: 1, …, C$\}$, where C is the number of retail chains, and $s_{ct,i} = 1$ if the household's category purchase occurred at t in retail chain c and 0 otherwise). With the assumption that $\varepsilon_{jt,i}$ is an i.i.d. extreme value, the probability takes the form of a standard multinomial logit choice (McFadden 1974). As we have noted, we fit our model to purchases made across retail chains, but because not all brands are available in all chains (i.e., on each purchase occasion t of consumer i), we introduce the indicator variables $z_{jt,i}$, which equal 1 if brand j is available to consumer i on purchase occasion t and 0 otherwise. Moreover, because each chain represents a different choice context, with potentially different error variances, we introduce a vector of chain-specific scaling parameters $\tau=\{\tau_c\}$, as suggested by Swait and Louviere (1993). The probability that consumer i chooses brand j on purchase occasion t, conditional on $\{\Omega_i, \tau, E_{t,i}, S_{t,i}\}$, is then:

$$\Pr\left(d_{jt,i}=1\,|\,\Omega_i,\tau,\mathrm{E}_{t,i},S_{t,i}\right)=\frac{z_{jt,i}\exp\left(\tau_c\left(-\exp\left(-r_i\left(\mu_{jt,i}-r_i\frac{\sigma^2_{jt,i}}{2}\right)\right)+X_{jt,i}\beta_i\right)\right)}{\sum_{k=1}^{J}z_{kt,i}\left(\exp\left(\tau_c\left(-\exp\left(-r_i\left(\mu_{kt,i}-r_i\frac{\sigma^2_{kt,i}}{2}\right)\right)+X_{kt,i}\beta_i\right)\right)\right)}. \quad [3.13]$$

To accommodate unobserved household heterogeneity, we use a random effects specification, with a normal distribution for the parameters $q_{j,i}$ and β_i and a lognormal

[10] Because consumption signals $G_{jt,i}$ are observed by the consumer, he or she knows the mean quality evaluation $\mu_{jt,i}$ deterministically. Meanwhile, the researchers does not observe consumption signals $G_{jt,i}$, so $G_{jt,i}$ appears as a random normal variable. Therefore, from the researcher's perspective, $\mu_{jt,i}$ is also a stochastic normal variable, and consumption signals must be integrated out (see Erdem and Keane 1996).

distribution (to ensure positive values) for the parameters $\sigma_{g,i}$, b_i, and r_i. We denote the means and standard deviations of $q_{j,i}$ and β_i as ($\nu_{q_j}, \varsigma_{q_j}$) and ($\nu_{\beta}, \varsigma_{\beta}$), respectively. Similarly, the means and standard deviations of the logs of $\sigma_{g,i}$, b_i, and r_i are ($\nu_{\sigma_g}, \varsigma_{\sigma_g}$), ($\nu_b, \varsigma_b$), and ($\nu_r, \varsigma_r$), respectively. In addition, σ_0^2 must be homogenous for identification purposes, and we keep φ, κ, and $\{\tau_c\}$homogeneous for the sake of model stability and tractability. Thus, our random effects model contains the listed means and variances as parameters, as well as σ_0^2, φ, κ, and τ. We estimate these parameters using simulated maximum likelihood. Appendix 2 provides details pertaining to the log likelihood and model estimation procedure (similar to Mehta, Rajiv, and Srinivasan 2004).

3.4 Empirical Analysis

3.4.1 Data

We calibrate the model on Gfk household panel data in the dish soap category (for manual cleaning of dishes). The total panel includes 630 households, and tracks their purchases over 130 weeks, in nine Dutch retail chains. In each category, we select households for whom at least two purchases were recorded. Moreover, because of our interest in reputation spillovers among different chain-specific PL brands, we only retain households that purchased the category in at least two different chains. 195 households satisfy these criteria. We consider the top five NBs (see e.g. Briesch et al. 2002, Chintagunta 2002 for a similar approach), as well as the (regular) private labels offered by the included retail chains. Together, these brands constitute 96% of category purchases in the nine chains in the sample.

As we show in Table 3.1, substantial variation exists among national brands in terms of both market share and unit prices, the latter ranging between 2 and 3.2 Euros per 500 grams. The leading national brand National Brand 1 captures more than one-third of category sales, at a premium price, followed by National Brand 2 with a 17.3% share and a medium price level.

The PLs exhibit an interesting pattern of prices and category purchase shares across the nine retailers. Only three of the private label brands (PL1, PL2 and PL5), each representing about 8% of the sampled shoppers' category purchases, are exclusive to a particular retailer. Private Label 1 (PL1) is offered by the largest national chain (positioned as a "service" retailer and capturing about 34% of grocery market sales in the Netherlands), at a price only slightly below that of National Brand 1. PL2 and PL5, in contrast, are own brands associated with two mid-market, value-oriented chains, at a substantially lower price.

TABLE 3.1. BRAND DESCRIPTIVE STATISTICS

	Share of Sample Purchases (in %)	Price (in Euro/500g)	Share of households never buying a brand during promotion
Private label 1	7.9	3.1	80.0
Private label 2	7.6	2.3	8.1
Private label 3	3.2	2.1	8.2
Private label 4	4.3	2.3	36.4
Private label 5	8.7	2.0	10.9
National brand 1	37.9	3.2	12.0
National brand 2	17.3	2.5	11.4
National brand 3	5.4	2.0	16.3
National brand 4	3.2	3.1	4.3
National brand 5	4.3	3.0	8.2
Total	100.0		15.0

Two private labels, PL1 and PL2 carry the name and logo of the retail chain. The remaining PLs are not labeled after a specific chain. PL3 belongs to the retail holding encompassing chains 3, 7 and 8, which are mid-market chains of neighborhood supermarkets, and is distributed through these three chains under a common label. Similarly, PL4 is shared by and made available through chains 2 and 9, which operate rather up-market, resp. medium and larger-sized supermarket stores.

Model free evidence

We first provide some model-free insights into the households' patterns of NB and PL purchases over time, and across the different chains. Of the sampled shoppers, 7% always purchase a private label dish detergent, while 36.4% are exclusive national brand buyers in the category, the majority (57.6%) adopting both PLs and NBs. This distribution is comparable to that in the total panel, with 119 (19%) PL, (31%) NB and 313 (50%) mixed buyers, indicating that our sample is not heavily skewed towards PL-prone households. Moreover, the share of PL brands in the sample's total dish detergent purchases amounts to 31.3%, a figure close to the category PL share in the total panel (42%), and comparable to the national PL share average across categories (19% AC Nielsen 2003).

As indicated above, our focal question is how PL consumption experiences in one chain, shape consumers' subsequent quality beliefs about and choice share of the PL of a rival chain. With this in mind, the primary question is whether we observe consumers that allow us to identify such a phenomenon. To this end, we need households who shop in multiple stores and buy PL brands. Table 3.2 shows that all selected households shopped in at least two chains, and that about 33% of households visited more than 2 chains. About 64% of households bought at least one PL brand, and more than 35% of households bought two or more different PL brands.

TABLE 3.2. NUMBER OF CHAINS VISITED (Panel a) AND NUMBER OF DIFFERENT PRIVATE LABEL BRANDS BOUGHT (Panel b) PER HOUSEHOLD

Panel a: Visited chains			Panel a: Different Private Labels bought		
Number of different chains	Number of households	Share of households	Number of different private label brands	Number of households	Share of households
2	116	67.0	0	63	36.4
3	44	25.4	1	49	28.3
4	11	6.4	2	53	30.6
5	2	1.2	3	7	4.0
			4	1	0.6

Next, it is interesting to observe that there is substantial within-household variation in the PL share of purchases across the patronized chains. For instance, considering the two most visited chains for each household (and leaving out the chain that does not carry a store brand), we find an average 20.3% difference in households' PL dish detergent purchase shares across the two chains, which is quite substantial. Similarly, the correlation across households between PL share in the most and second most visited chain is 75.8%, a figure significantly different from 1 ($p<.01$). Hence, the probability that a PL is selected upon a dish detergent purchase is not simply a household trait.

Second, households' PL purchase shares within a visited chain also vary considerably over time. To see this, we subdivide our 130 weeks of observations into four sub-periods (of about 32 weeks each), and calculate the PL category purchase share for each household in each chain visited in the sub-period. Next, we compute, for each household and visited chain, the standard deviation of this PL share across the four sub-periods. Table 3.3, panel a, provides summary statistics by chain. It indicates that households' PL share of dish detergent purchases in a chain vary considerably across the four sub-periods (pointing to within-household, within-chain, over time variation), for chains with low as well as high average PL purchase shares.

A third question, then, is what drives these dynamics. As the large portion of households (66%) never made a PL purchase during a promotion, this over-time variation cannot be entirely attributed to deals. Instead, we find that households who are heavy category PL buyers in a certain sub-period (over 30% of dish detergent purchases allocated to PLs), are significantly more likely to become heavy PL purchasers in the next 32-week period in a chain not visited before and, hence, in which they have no own-chain PL experience ($\chi^2=8.483$, $p<.01$). Of course, given that this test does not control for specific store, household, and marketing mix variables, it is at best roughly indicative of cross-store PL effects. To cleanly separate out cross-store PL learning from other factors, we estimate a choice model with Bayesian cross-learning – as reported below.

TABLE 3.3: WITHIN HOUSEHOLD VARIATION IN PL PURCHASE SHARE OVER TIME, BY CHAIN

Chain	Number of households	PL purchase share	
		Average	Within-household standard deviation
1	103	.311	.075
2	14	.235	.022
3	52	.313	.102
4	94	.346	.117
5	48	.600	.123
6	-	-	-
7	23	.327	.041
8	16	.198	.102
9	35	.161	.071

[a] Calculations in this table only include households who visited the chain at least once in 32-week sub period. [b] Standard deviation of the household's PL share in the chain, calculated over four 32-week sub periods, and then averaged over households visiting the chain.

3.4.2 Estimation Results

Model fit and validity. We compare the fit and predictive performance of our proposed model against two benchmark models. The first benchmark, M0, uses the updating Equations [3.6] and [3.7] for all brands and thus does not include cross-brand learning. In the second benchmark, M1, we allow for cross-brand learning but only independent of perceived brand similarities by using updating Equations [3.10] and [3.11] for PL brands but setting the contingency parameter κ to 0. Our full model, M2, features conditional cross-brand learning, Equations [3.10] and [3.11] as updating expressions for PL brands, and φ and κ as estimated (ceiling and contingency) parameters.

As we indicate in Table 3.4, the proposed (full) model M2 outperforms the benchmark model M0 across the board. In line with our expectation, accommodating for cross-brand learning among PL brands leads to a higher log-likelihood and hit-rate, lower Bayesian information criterion, and lower Akaike information criterion in the estimation sample, as well as a higher log-likelihood and hit-rate in the holdout sample. Moreover, the full model M2 improves on the benchmark M1 in the estimation and holdout samples in terms of log-likelihood and has comparable hit-rate, which confirms that spillovers among PLs depend on their perceived quality differences.

TABLE 3.4 FIT AND PREDICTIVE VALIDITY FOR FULL AND BENCHMARK MODELS

	Benchmark Model M0 No PL Cross-Brand Learning	Benchmark Model M1 Non-contingent PL Cross-Brand Learning	Full Model M2 Contingent PL Cross-Brand Learning
Log-likelihood	-705.0715	-701.6975	-697.1569
Hit rate	0.64216	0.65701	0.65582
Bayesian information criterion	1726.2982	1726.0686	1725.8911
Akaike information criterion	1492.1430	1486.2023	1480.3138
Log-likelihood in holdout sample	-187.8055	-184.0929	-181. 3252
Hit rate in holdout sample	0.61241	0.63131	0.63022

To validate our model, we perform a series of robustness checks. First, we run a model with cross-brand learning for not only PLs (as in M1 and M2) but also NBs. Second, we compare our model with a simpler model that captures dynamics in brand choices through a last purchase variable instead of learning and forgetting. Third, because cross-brand learning among PLs could reflect consumers' tendency to buy brands with similar (price) positioning, or stated differently, be loyal to a price tier, we augment the full model with a variable that captures the absolute difference between the price of the focal brand and the brand previously bought by a household. Fourth, what we refer to as brand type (PL-based) learning conceivably could stem from consumers' quality inferences based on price when they have little knowledge about a brand. To rule out this possibility, we augment our model with price-based learning using a specification similar to Erdem and colleagues' (2008).[11]

The results of these robustness checks are strongly encouraging. Cross-brand learning among NBs is virtually absent, regardless of brand similarity. Moreover, in each of the four cases, we find support for our expectations: our full model still offers an improvement in fit and predictive validity over alternative specifications. Also, the magnitude of the forgetting (ν_b), risk aversion (ν_r), and learning (ν_{σ_η}, log(1/(φ – 1), log(κ)) coefficients do not change substantially; therefore, our conclusions remain largely unaffected. In all, these extensions provide strong support for contingent cross-brand learning among PL brands.

Parameter estimates. In Table 3.5, we report the parameter estimates for the full model. The coefficients appear to have face validity. The promotion sensitivity parameters (feature only: $\nu_{\beta_{FO}}$ = 2.85, $p < .01$; display only: $\nu_{\beta_{DO}}$ = 2.38, $p < .01$; feature and display: $\nu_{\beta_{FD}}$ = 3.32, $p < .01$) are all significant and positive, and the impact of price is negative (ν_{β_P} = -.96, $p < .01$). The brand quality parameters reflect the population mean of true brand quality relative to brand National Brand 1. The parameters related to consumer learning are in line with previous findings, and the standard error of the consumption signal (ν_{σ_g} = .83) achieves a similar order of magnitude to that reported by Erdem (1998) and Erdem, Keane, and Sun (2008). The rate of forgetting (ν_b = 7.02) also is comparable to that found by Mehta, Rajiv, and Srinivasan (2004): They report that it takes 19.8 weeks for the information learned through consumption to depreciate to half of its value; we find an average value of 26.1 weeks.

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[11] The exact specification of this model is available from the first author upon request.

TABLE 3.5 PARAMETER ESTIMATES FOR THE FULL MODEL M2

	Mean Across Households			Standard Deviation Across Households		
	Symbol	Parameter Estimate	S.E.	Symbol	Parameter Estimate	S.E.
True Brand Quality						
Private Label 1	ν_{q_1}	1.40	.23	ς_{q_1}	.49	.04
Private Label 2	ν_{q_2}	1.50	.23	ς_{q_2}	.44	.06
Private Label 3	ν_{q_3}	1.11	.24	ς_{q_3}	.10	.06
Private Label 4	ν_{q_4}	1.14	.23	ς_{q_4}	.23	.03
Private Label 5	ν_{q_5}	1.10	.22	ς_{q_5}	.72	.08
National Brand 1	ν_{q_6}	1.00	fixed	ς_{q_6}	.11	.01
National Brand 2	ν_{q_7}	.70	.27	ς_{q_7}	.32	.03
National Brand 3	ν_{q_8}	.83	.29	ς_{q_8}	.18	.06
National Brand 4	ν_{q_9}	.59	.38	ς_{q_9}	.18	.07
National Brand 5	$\nu_{q_{10}}$	.73	.27	$\varsigma_{q_{10}}$	.04	.06
Other Determinants of Utility						
Feature and display	$\nu_{\beta_{FD}}$	3.32	.78	$\varsigma_{\beta_{FD}}$	.32	.03
Feature only	$\nu_{\beta_{FO}}$	2.85	.92	$\varsigma_{\beta_{Fo}}$	.14	.21
Display only	$\nu_{\beta_{DO}}$	2.38	.83	$\varsigma_{\beta_{DO}}$	.62	.05
Price	ν_{β_P}	-.96	.50	ς_{β_P}	1.55	.39
Learning and Forgetting						
Log of standard error of consumption signal	ν_{σ_g}	.83	.24	ς_{σ_g}	.42	.00
Log of forgetting parameter b	ν_b	-7.02	.72	ς_b	3.04	.00
Log of risk aversion parameter	ν_r	.45	.17	ς_r	.29	.08
Transformed ceiling parameter	log(1/(φ - 1))	-1.29	.50			
Log of contingency parameter	log(κ)	2.66	.19			
Variance of quality belief at t = 0	ν_0	1.00	fixed			

TABLE 3.5 CONTINUED

	Symbol	Parameter Estimate	S.E.
Chain-Specific Scaling Parameters			
Retailer 1	log(τ1)	.00	fixed
Retailer 2	log(τ2)	-.99	.74
Retailer 3	log(τ3)	.14	.54
Retailer 4	log(τ4)	-.11	.43
Retailer 5	log(τ5)	-.07	.52
Retailer 6	log(τ6)	.51	.58
Retailer 7	log(τ7)	.20	.61
Retailer 8	log(τ8)	-1.00	.55
Retailer 9	log(τ9)	-.30	.53

Focusing on the PL cross-brand learning parameters (i.e., ceiling and contingency), we find that the transformed ceiling parameter $\log(1/(\varphi - 1))$ equals –1.29 (see Table 3.5), which corresponds to a φ level of .78. Therefore, among PL brands perceived as having the same quality, consumers incorporate 78% of the consumption signals from one PL brand to update their beliefs about others. The estimated log of the contingency parameter, $\log(\kappa) = 2.66$, indicates that the degree of cross-brand learning clearly is contingent on perceived brand similarity.[12]

To clarify the magnitude of the effects, we compare the impact of cross-brand learning on a PL brand's choice probability with that of within-brand learning. For the most dissimilar PL brands in the sample, for which perceived similarity is the weakest, cross-brand spillovers result in choice probability changes that are 5–10% of the changes that result from within-brand learning. For the most similar PL brand pairs however, this figure rises dramatically to 60–70%, which suggests that cross-brand learning is not only a statistically significant but also

[12]Again, $\kappa = 0$ would point to noncontingent transfers across *all* private labels.

a managerially relevant phenomenon. Below, we shed further light on the implications of this cross-brand learning for PLs, depending on their quality positioning.

3.5 Reputation spillovers and PL quality positioning

We have established that cross-brand learning among PLs takes place and that its magnitude depends on the perceived similarity of PL brands. In this section, we focus on the implications of this phenomenon for retailers (RQ3). In essence, the presence of cross-brand learning among PLs implies that retailers face reputation spillovers, which may take the form of either quality belief or familiarity spillovers. The sign and magnitude of those spillovers depends on the positioning of a given retailer's PL brand relative to other PL brands.

3.5.1 Quality Belief and Brand Familiarity Spillovers

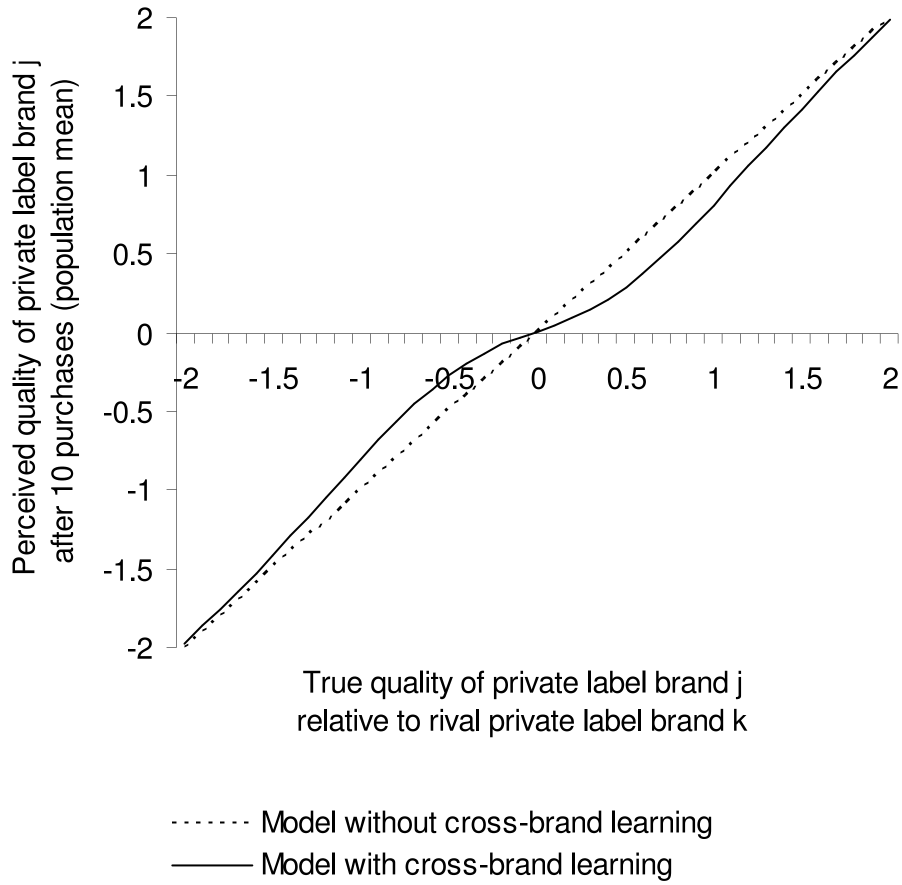
The sign and magnitude of quality belief spillovers for a given PL brand depend on whether it is of a higher or lower quality than other PL products. Quality belief spillovers are positive for PL brands situated at the low end of the market, because their average quality belief gets inflated on the basis of consumption signals from other, higher-quality PL brands. However, the situation is opposite when the spillover-receiving brand is of a higher quality than other PL brands adopted by the consumer, because the consumer believes the high-quality PL brand is worse than it actually is, on the basis of the low-quality signals from other PL brands. The risk reduction brought about by familiarity spillovers, in contrast, is always positive, and only the size of such spillovers depends on the PL's quality position relative to others.

To illustrate these phenomena, we conduct a simulation. We consider a simple setting with two PL brands: k, whose true quality population mean is fixed at 0, and j, whose true quality population mean ν_{q_j} varies across simulation scenarios from –2 to 2. Thus, the maximum difference between the brands' qualities is 2. (This value should be considered in the context of our data, for which the maximum difference between estimated true quality population means is .4, and the standard deviations in the population range between .1 and .49.)

Each PL brand appears in a different chain, and consumers choose those chains randomly during each purchase occasion. For every quality level of brand j, we generate purchase histories that consist of 10 subsequent purchases by 100 heterogeneous consumers who, depending on the chain visited, purchase brand k or brand j. After each purchase/consumption occasion, we update the mean and uncertainty of the quality beliefs for both brands following the model without cross-brand learning (Equations [3.6] and [3.7]) and the model with contingent cross brand learning (Equations [3.10] and [3.11]) using (random draws from distributions of) parameter estimates from the previous section. We then report for each scenario (i.e., true quality population mean of brand j) the mean and variance of perceived quality for brand j on the tenth purchase occasion, averaged across 100 purchase histories times the 100 random draws of parameter values and consumption signals.

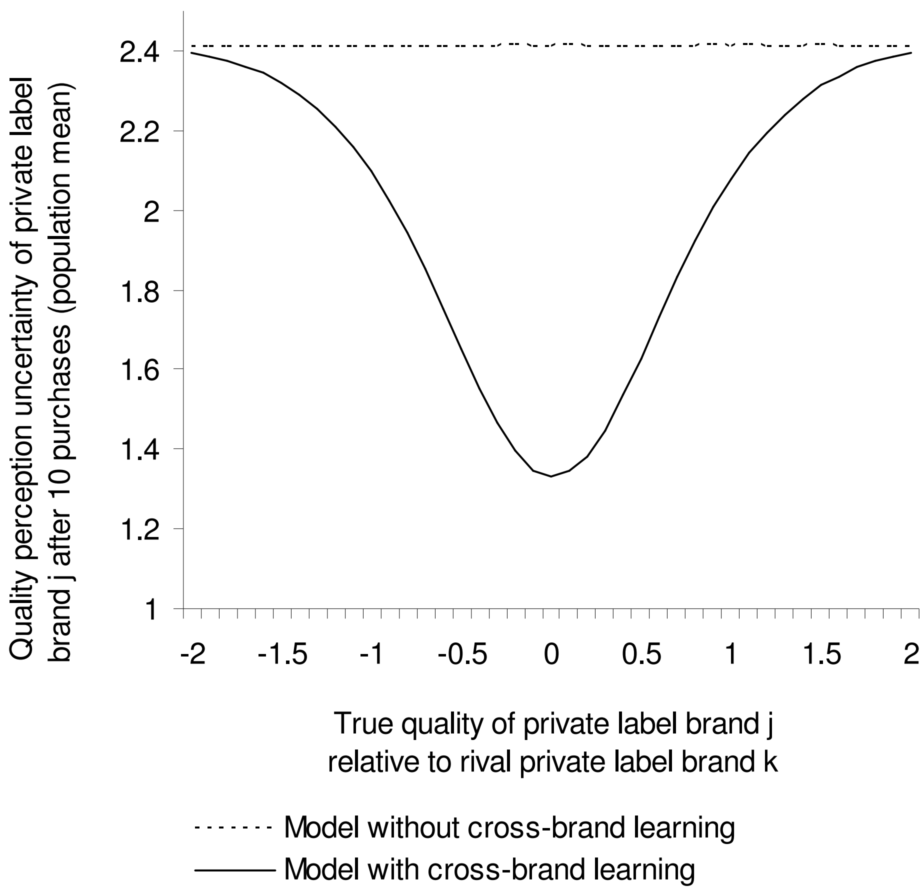
In Figure 3.1, we depict the average perceived quality of brand j (μ_{jt}, y-axis) as a function of its true quality position relative to brand k (x-axis) $\nu_{q_j} - \nu_{q_k}$. In the absence of any cross-brand effects, the mean quality beliefs for brand j follow the 45° line. The deviation of the plotted line reflects quality belief spillovers.

FIGURE 3.1 QUALITY BELIEF SPILLOVERS AS A FUNCTION OF QUALITY POSITIONING IN THE PRESENCE AND ABSENCE OF CROSS-BRAND LEARNING



Note: In a setting with two private label brands j and k, the figure plots on the x-axis the true quality of brand k relative to brand j (whose true quality is zero), on the y-axis the perceived quality of brand j after a (simulated) 10-period purchase history, without (dotted line) and with (solid line) cross-brand learning. Deviations between the solid and the dotted line represent positive (left side) or negative (right side) quality belief spillovers from brand k to brand j.

FIGURE 3.2 FAMILIARITY SPILLOVERS AS A FUNCTION OF QUALITY POSITIONING IN THE PRESENCE AND ABSENCE OF CROSS-BRAND LEARNING.



Note: In a setting with two private label brands j and k, the figure plots on the x-axis the true quality of brand k relative to brand j (whose true quality is zero), on the y-axis the quality belief uncertainty of brand j after a (simulated) 10-period purchase history, without (dotted line) and with (solid line) cross-brand learning. Deviations between the solid and the dotted line represent familiarity spillovers from brand k to brand j.

When the true quality of brand j is 0 (that is, equal to the true quality of brand k, $\nu_{q_j} = \nu_{q_k} = 0$), the plotted curve crosses the 45° line, because cross-brand learning does not lead to any bias in brand j's quality beliefs. For quality levels of brand j that are less than 0, the average quality belief spillovers are positive, and the plotted line rises above the 45° line;

the opposite holds if the true quality of brand j exceeds that of brand k (i.e., exceeds 0), such that quality belief spillovers from brand k are negative (plotted line below the 45° line). The quality belief spillovers become small in absolute value if brands are of very different quality (extreme values on the x-axis), and the degree of cross-learning declines because of their low perceived similarity (see Equation [3.12]).

In Figure 3.2, we present the uncertainty (variance) in quality beliefs for brand j at the end of the simulated purchase history (σ_{jt}, y-axis) as a function of its quality positioning relative to the rival PL brand k (x-axis); again, the true quality of brand k is 0. For comparison purposes, we also plot the quality belief variance in a scenario without cross-brand learning,[13] using simulations similar to those described previously. For any given quality level of brand j, the distance between both curves indicates the amount of familiarity spillovers. As we expect, these familiarity spillovers reduce consumers' uncertainty about the quality of brand j (solid line situated below the dotted line)—even more when both brands have equal quality (0 on x-axis).

3.5.2 Net Spillovers and Quality Positioning

We thus show that cross-brand learning induces two types of reputation spillovers—quality belief and familiarity—that depend on the relative quality positioning of PLs. Next, we investigate the net impact of these spillovers on PLs' utility as a function of their positioning strategy.

PL quality positioning and impact of cross-brand learning on PL utility. Three potentially interesting strategies for PL quality positioning emerge from our findings. First, quality belief spillovers appear most beneficial when a PL brand's quality position is slightly below that of other PL brands. Such a positioning allows the brand to free-ride on the quality of rival PL brands. Yet there are limits to this free-riding positioning. Because positive quality

[13] In this case, uncertainty σ_{jt} does not depend on brand j's quality but corresponds to a horizontal line in the figure.

belief spillovers disappear for products located at the very bottom of the quality spectrum, brands lagging in terms of quality appear to get recognized as negative outliers.

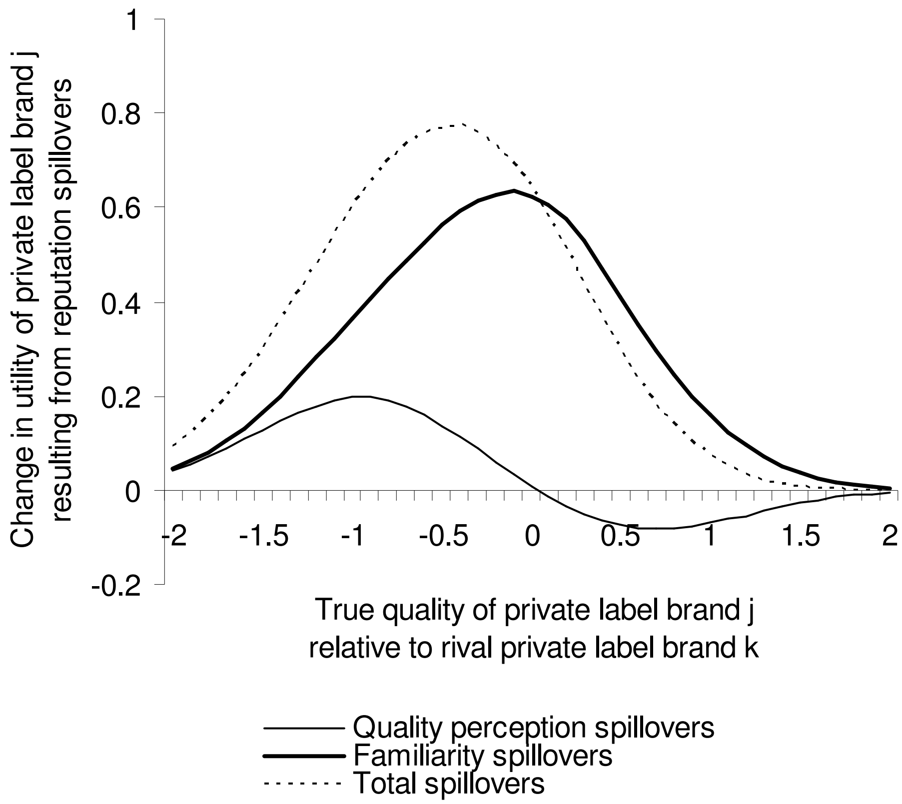
Second, though medium-level upscale PL brands experience harmful low quality spillovers from rival brands, PL brands located at the top of the quality spectrum avoid such negative externalities. That is, it appears that retailers occupying a substantially higher position than other PL brands can clearly distinguish themselves as quality leaders by adopting quality leader positioning.

Third, consumption of a PL brand reduces the quality uncertainty for other PL brands, and this especially when the spillover-yielding and spillover-receiving brands are perceived as similar. PL brands thus maximize the benefits of familiarity spillovers when positioned closely to other PL brands, a strategy that we refer to as the herd positioning.

The benefits of these strategies depend on the relative impact of both types of reputation spillovers. As Equation [3.10] reveals, increases in the mean quality beliefs of the PL (μ_{jt}, caused by quality belief spillovers) and reductions in uncertainty (σ_{jt}, caused by familiarity spillovers) both positively influence the PL's utility and resulting choice share. When quality belief spillovers dominate familiarity spillovers, the free-riding approach offers the most beneficial cross-effects. Conversely, when familiarity spillovers dominate, herd positioning results in the greatest reputation gains. The relative magnitude of both types of effects is an empirical question that depends on the observed level of risk aversion.

To assess the net spillover effects for our setting, we again use simulations. We calculate the mean and variance of quality beliefs for brand j at the tenth purchase occasion, as well as the associated brand utility. The difference in brand utility implied by the two models, with and without cross-brand learning, is the total effect of reputation spillovers. It can be decomposed into the effect of quality belief spillovers (utility change due to a difference in μ_{jt}) and the effect of familiarity spillovers (utility change due to a difference in σ_{jt}).

FIGURE 3.3 REPUTATION SPILLOVERS AS A FUNCTION OF QUALITY POSITIONING



Note: In a setting with two private label brands j and k, the figure plots on the x-axis the true quality of brand k relative to brand j (whose true quality is zero), on the y-axis the change in utility of brand j after a (simulated) 10-period purchase history, resulting from quality belief spillovers (positive or negative: thin solid line), familiarity spillovers (positive: thick solid line), and the sum of those two (positive: dotted line).

In Figure 3.3, we depict the impact of spillovers on the utility of brand j (y-axis) as a function of its quality positioning relative to brand k (x-axis) for the estimated population mean level of risk aversion (ν_r = .45). Familiarity spillovers dominate quality belief spillovers, revealing a positive total effect of cross-brand learning on utility. Even when brand j adopts a quality positioning slightly above that of brand k (values greater than 0 on the x-axis) and experiences negative quality belief spillovers, the positive familiarity spillovers more than compensate. A similar pattern emerges when we use the lower bound of the 95% confidence interval for the population mean risk aversion parameter (i.e., ν_r = .12): lower risk aversion reduces the importance of familiarity spillovers relative to that of quality spillovers for brand utility, but the general pattern remains unchanged, which underscores the benefits of the herd—or even better, herd plus some free–riding—positioning.

PL quality positioning, cross-brand learning, and PL and NB choice shares. From the above, it appears that PLs primarily benefit from reputation spillovers from rival PLs, because as consumers use and learn about PL brands, they enjoy reduced uncertainty that in turn influences their choices inside the store. National brands do not enjoy such cross-brand benefits[14] but instead must earn their own reputations individually, which may put them at a disadvantage, especially if the PL brands are positioned close together.

To illustrate this point, we run an additional simulation that considers three brands: the two PLs used previously and a NB n available in both chains. For illustrative purposes, the NB's quality is fixed at 0 (ν_{q_n} = 0). We again simulate consumer purchase histories and consider the outcomes for different PL quality positions implied by the models with and without cross-brand learning. However, this time, we focus on the choice shares of the three brands (two PLs and one NB) as the variables of interest.

In Figure 3.4, we summarize our findings. Taking the no cross-PL learning scenario as the reference setting (0 value on the y-axis), we show the change in the choice shares of the three brands that results from cross-brand learning among the PLs (y-axis), as a function of the quality differences between PL brands (x-axis).

[14] Our robustness checks show no cross-brand learning for national brands.

FIGURE 3.4 CHANGE IN BRANDS' CHOICE SHARE RESULTING FROM CROSS-BRAND LEARNING, AS A FUNCTION OF QUALITY POSITIONING

Note: In a setting with two private label brands j and k and a national brand n, the figure plots on the x-axis the true quality of brand k relative to brands j and n (both with true quality zero), on the y-axis the change in choice share of brand j (gain: thin solid line), brand k (gain: thick solid line), and brand n (loss: dotted line).

Cross-brand learning among private labels reduces the choice share of the NB, as depicted by the dotted curve situated below 0. The drop in the NB's share is greatest when the PL brands are most similar (i.e., 0 quality for both brands on the x-axis), which illustrates how PL brands collectively can gain share over national brands by jointly generating consumer familiarity.

It is important to note that the dying out of the cross-brand learning effect occurs for quality differences substantially larger than what we observe for most consumers and brands in our sample. Specifically, the largest PL brand quality difference for an average consumer is .4, and dying out occurs for quality differences that are three to four times larger. Such quality differences are observed only for a fraction of our sampled households.

3.6 Conclusions, Limitations, and Further Research

Current literature features an ongoing debate about the extent to which PLs constitute an instrument for retailer differentiation. Although some researchers suggest PL brands set retailers apart (Corstjens and Lal 2000; Marketing News 1987), others contend that consumers simply view PLs as homogeneous and interchangeable across chains (Ailawadi and Keller 2004; Richardson 1997). This debate therefore prompts intriguing questions: Are PLs private, that is, do consumers distinguish among PLs offered by different retailers, and to what extent are their beliefs shaped by each PL's specific quality positioning? We expect that consumers classify different PL into a single mental category and gauge the quality of specific PLs on the basis of their experiences with other members of the category, that is, rival PL products. However, the strength of such cross-brand learning may depend on the precision of consumers' brand knowledge and the brands' true quality differences. To test these propositions, we develop a dynamic brand choice model with cross-brand quality learning and calibrate it with a panel data set pertaining to liquid dish detergent purchases in multiple chains.

Our findings confirm that PLs are not all that private. Consumers use their experiences with one PL brand to update their beliefs about other brands, which does not occur among NBs. This cross-brand learning among PLs results in two types of reputation spillovers. First, consumption experiences with one PL brand cause consumers to revise their mean quality beliefs about other PL products, which we refer to as quality belief spillovers. These spillovers are positive for PLs with slightly worse quality but negative for higher-end brands. Second, consumption of one PL reduces consumers' uncertainty about the quality of other PL products and, because of their risk aversion, increases the appeal of these products because of familiarity spillovers. We find clear evidence for both types of spillover phenomena. Our estimates also confirm that reputation spillovers are not equally strong among all PL brand pairs: more pronounced true quality differences among brands decrease their importance drastically. Although low-quality PL brands can free-ride through quality belief spillovers, a clear limit marks the possibilities for free-riding: When consumers perceive a PL's quality as significantly inferior to that of other PL brands, they no longer allow quality beliefs to spill over onto it. To take advantage of familiarity spillovers, brands should embrace a herd strategy and position themselves close to other PL brands. Thus, overall, PL products that occupy a slightly below-average quality position compared with rival private label brands (a 'herd with free-riding' approach) capitalize best on both types of reputation spillovers.

The presence and nature of cross-brand learning have important management implications. PL quality and reputation investments by a retailer appear to benefit other retailers, but is this benefit a positive or negative phenomenon? On the one hand, reputation spillovers constitute a pitfall, because they limit the potential of PLs to differentiate retailers. Retailers that hope to use a PL as a chain differentiating tool therefore must pursue a quality leadership strategy, which diminishes the subsidy of rival brands and prevents the threat of negative quality belief spillovers. In order to break away from such negative quality belief spillovers, retailers should aim at a sizable quality gap, which is substantially larger than the one we observe in the data for most consumers.

On the other hand, such a quality leader positioning entails the loss of certain benefits associated with cross-brand learning. In our empirical application, we find that 'not being private' is beneficial to all private label brands in the data set, in that it enhances the PLs 's choice share among consumers who buy from the category in the store. This overall positive effect results from the predominance of 'familiarity spillovers'. That is, it appears consumers use and learn about the concept of PL brands, which reduces their uncertainty about PL products and enhances their choice propensity relative to NBs.

Middle-of-the-road retailers thus may find it optimal to provide customers with mainstream PL offers and enjoy mutually beneficial effects that the NBs cannot share: the wider establishment of PLs across chains strengthens their choice shares in comparison with NBs. In contrast, high-end retailers may prefer a superior quality image for their PLs. However, in selecting this option, retailers would have to not only establish a brand reputation on their own but also distance themselves from the mainstream PL quality image.

Our study contains several limitations that set the stage for intriguing new research. First, to shed light on the role of PLs in retailer differentiation, we focus on the differentiation of PL brands and implications for brand choice. Yet as our results show, high-quality PLs may be perceived as distinct from rival retailer brands, so research should gauge the effect of PL appeal and investments on retail chain differentiation, as well as on store choice and store margins.

Second, our empirical results pertain to only one category, and further research could document determinants of the strength of cross-brand learning in different product categories. For example, the rate of cross-brand learning among PLs may depend on category characteristics, such as quality uncertainty, perceived within-category quality differences, purchase frequency, or the degree of cross-chain shopping. We also expect that category-related drivers could influence the relative importance of familiarity versus quality belief spillovers, such that products with high levels of risk aversion (quality sensitivity) involve more pronounced familiarity (quality belief) spillovers.

Third, we do not study cross-category effects in consumer learning, which are suggested by Sayman and Raju (2004), who find cross-category promotional effects for PLs, and by Ailawadi and Keller (2004). Incorporating cross-category and cross-retailer consumption-based spillovers in one single model is a very challenging task. First, it would require the analysis of data covering purchases of a broad set of categories and retailers simultaneously. A second, more problematic, issue is that a model with simultaneous cross-PL and cross-category spillovers would become intractable - adding another dimension to an already complicated model structure. The important question here is whether not accounting for such cross-category effects in the current model, biases the within-category cross-store learning effect estimates. Since the cross-PL learning effects are based on purchase dynamics (please note that cross-sectional differences between households would show up through heterogeneity in brand appeal), a possible bias in these effects would have to stem from over-time correlations, between (1) a given household's purchases of rival PLs in the same category (our current cross-effects), and (2) that household's purchases of the same-chain PL in other categories (which would drive the cross-category effects). Our contention is that our cross-PL effect would be biased upward only if purchases (1) and (2) coincide (have a strong positive over-time correlation), in which case the PL cross-learning part of the specification would pick up some of these cross-category effects. If, however, these purchases (1) and (2) are not aligned in time, we do not expect such an upward bias and, with negatively correlated purchase sequences, the cross-PL effect might even be underestimated. Since consumers are more likely to visit stores sequentially rather than simultaneously, and often group purchases of different categories on a single store visit, we would not expect strong positive correlations between the timing of purchases (1) and (2) for a given household. As an additional robustness check, we could collect data on households' other-category PL purchases for each of the different chains. We could then augment the model with a control variable, summarizing the household's number (fraction) of same week-same store PL purchases in other categories, and check whether the cross-learning PL effects remain, indeed, unaffected. Given the importance of this data collection task, we leave this as a next research step.

Fourth, our specification allows quality differences to drive the perceived similarity between pairs of PL brands, which, in turn, moderates the magnitude of cross-brand learning. Further studies, however, should also investigate the role of other instruments. For example, advertising messages could affect consumers' beliefs of PL differences and stimulate or help avoid reputation spillovers. PL branding strategies may also reveal important: retailers setting out to avoid negative reputation effects from rival PL brands could choose brand names that are not readily identifiable as private labels.

Fifth, other aspects of retail strategy may shape the degree of PL spillovers. Our study pertains only to traditional supermarkets, but it might be interesting to investigate the extent of cross-brand learning among retailers that differ in their price or quality positioning (e.g., Hi-Lo supermarkets versus hard discounters) or operate different size formats (e.g., supermarkets versus superstores). Moreover, an emerging retailer strategy is to offer, next to their ‘standard’ quality PL, low-end (economy) and premium store brands. While this strategy is currently implemented by only a subset of (more innovative) retailers in a few categories, an interesting question is how the advent of such downscale and upscale versions will influence reputation spillovers. Will consumers abandon the notion of PLs as a mental category in response, or will they construct a separate category for each PL quality tier, with strong cross-chain effects in each tier? An interesting contention, based on our results, is that selling standard and premium private labels could offer retailers a way out of the caveat: while standard store brands could be designed so as to capitalize on familiarity spillovers, premium private labels might be used as an instrument to break away from negative quality spillovers from rival chains. As more data pertaining to different PL versions become available, studying these effects would be highly worthwhile.

Sixth, the model could be extended to accommodate more types of asymmetries in cross-brand learning. The currently used model allows for asymmetries stemming from differences in the level of brand quality uncertainty among the involved PL brands: brands that a consumer has more experience with being less influenced by spillovers from rival PLs. It is conceivable that asymmetries can also stem from other brand characteristics, such as differences in PL brand salience, or differences in the strength of association with the PL brand type (i.e. How easily is the brand recognized as a private label?). Preliminary results from more refined models suggest no difference in cross-learning between PL brands that are named after the retail chain and those that are not. A tentative explanation is that while the use of a chain name may make the brand more recognizable as a private label, it also creates stronger differentiation from rival PL brands by building on the reputation of the chain. Future research should shed more light on these mechanisms.

Seventh, while our cross-learning specification is quite flexible and exhibits descriptive as well as predictive validity, it is a ‘reduced form’ model that is somewhat ad hoc. A next step in the study of (contingent) cross-PL effects would be the use of a fully ‘structural’ specification, in which cross-effects result from a multivariate Bayesian updating mechanism, based on correlated priors (as in Erdem et al, 1998) or on correlated signals (see, e.g., Coscelli and Shum, 2004). Using these specifications for our purposes would call for a model extension to accommodate contingencies in the cross-PL spillovers. We are currently working on such an extension, and the preliminary results seem to confirm the findings of our reduced form model.

Finally, as remarked in Chapter one, we do not observe retailer policy changes in terms of quality repositioning, or new PL brands entering the category. As a result, we need to be careful in deriving strategic policy implications from our findings. In order to make normative claims, we would need to either analyze natural experimental settings in which major policy shifts occur, or develop a fully structural model in which not only consumer choices, but also retailer positioning strategies, are endogenous. As this would require far richer data sets or far more complicated models (in which not only within-category brand choice, but also store choice would need to be included, as a driver of retailer decisions), we leave such analyses for future study.

4 Copycat Private Labels: Friend or Foe? Quality Belief Spillovers and Choice Share Effects for Imitating Retailer and Imitated National Brands

4.1 Introduction

Many private labels in consumer packaged goods are modeled on leading national brands. Sayman, Hoch and Raju (2002) observed blatant package imitation by the private label in over one third of 75 consumer packaged goods categories. In a survey of national US supermarkets, Scott-Morton and Zettelmeyer (2004) found half of the store brands matching a national brand package at least in color, size and shape. Trade dress imitation also constitutes a deliberate strategy among multiple European retailers like Auchan in France, and Sainsbury in the UK (Kapferer 1995).

While the overall success of copycat private labels is well documented, the extent to which this can be ascribed to the imitation strategy is far less obvious. Apart from creating initial confusion about brand identity, retailers hope, through the copycat practice, to benefit from the quality image and reputation of the imitated national brands (Planet Retail 2007). Especially in cases where the imitation is not exact and not blatant enough to trigger visual confusion at the point of purchase (a strategy pursued by retailers to avoid instant litigation), such dynamic spillover effects would become the key driver of losses for national brand manufacturers. For these reasons, copycatting constitutes a major source of concern and even legal action on the part of leading manufacturers (Planet Retail 2007, Kapferer 1995). At the same time, the imitation strategy can backfire on the retailer if the quality gap between the original and imitating brand leads to contrast effects and an increase in evaluation of the original brand (Zaichkowsky and Simpson 1996), or makes consumers interpret the package similarity as an attempt to mislead them (Warlop and Alba 2004). Yet, even though the copycat phenomenon is widespread and its effects on the imitator and imitating brand are unclear, little empirical evidence is available on these implied reputation spillovers and their brand choice consequences, especially in actual choice settings. Based on the insights obtained from experimental studies, Warlop and Alba (2004) conclude that "… consumer reaction to persuasion cues [trade dress imitation] or persuasion agents is a complex phenomenon that justifies additional research".

Our research intends to address this gap, by focusing on the following research questions: Do consumers shape their quality beliefs of copycat private labels based on consumption experiences with the imitated national brand and, conversely, are quality beliefs of the imitated brand affected by copycat consumption? If quality belief spillovers from the original brand to the copycat are found, are these spillovers recurring, or do they dilute as consumers build up experience with this copycat? Last but not least, is there evidence of experience-based 'reactance', i.e. consumers refuting the imitating private label, or 'rewarding behavior', i.e. consumers assigning extra utility to the original brand, as they become aware of the true quality gap between the copycat and the imitated national brand?

To answer these questions, we develop a brand choice model that allows for dynamic cross-brand learning among the imitated national brand and the private label copycat, and accommodates possible post-consumption reactance or rewarding behavior. We study these effects for the commonly observed setting where the copycat's package similarity to the leading NB is clearly noticeable and intentional (i.e. stands out among other brands or the category trade dress code), but not exact. Taken together, our findings should help national brand manufacturers assess to what extent such PL imitations constitute a 'friend' (ultimately rewarding the original brand for being superior in quality and hard to imitate) or a 'foe' (stealing share by piggy backing on its quality reputation).

The discussion is organized as follows. In the next section, we develop a framework for the cross-brand learning effects between the copycats and the imitated national brands, bringing together insights from the literature. Section 3 then presents the models used to study these effects, and the estimation procedure. In section 4, we discuss the empirical setting, and report estimation results. Section 5 sheds light on the model implications for national brand and private label performance, while section 6, finally, formulates conclusions, and addresses limitations and future research areas.

4.2 Literature – Conceptual Framework

Visual characteristics or "Trade Dress" of a brand are important for its speed of identification in a cluttered environment and the accuracy with which it can be set apart from competitors (Richardson et al. 1994; van der Lans et al. 2008; Warlop and Alba 2004). Building on this premise, much research on trade dress imitation has studied whether it causes visual confusion: Do consumers inadvertently pick the copycat while believing they purchased the imitated brand? From a legal perspective, the presence of brand confusion has been a key criterion to judge whether imitation is harmful and therefore in violation of trademark protection (Foxman et al. 1992; Jacoby and Morrin 1998).

However, as indicated by Warlop and Alba (2004), such visual confusion is unlikely for copycats with a clearly distinguishable brand name from the original. Along the same lines, Howard, Kerin and Gengler (2000) indicate that the likelihood of confusion about a brand source association is strongly linked to similarity in the brand names. For umbrella private label brands, which carry across many categories and often have a clear reference to the retailer's name, brand name similarity to the imitated national brand is typically low, and the likelihood that consumers mistakenly buy the copycat because of the package similarity is therefore expected to be small. Moreover, apart from brand name indications, retailers tend to avoid packages that perfectly copy the original's color, shape, size *and* illustrations, as overly blatant imitations are bound to trigger manufacturer litigation (see, e.g., recent rulings against Lidl for copying Steinmann jewelry cases, or against Albert Heijn for selling peanut butter and margarine private labels too similar in design to the corresponding Unilever items (Planet

Retail 2007, p. 52). Instead, they stick to less pronounced trade dress similarity, which further reduces the likelihood of visual confusion.

This does not imply, however, that copycatting cannot be a successful strategy for the imitating private label brand, and that the leading national brand will not suffer from the imitation – or vice versa. As Collins-Dodd and Zaichkowsky (1999) indicate: "The basis of imitation is that consumers generalize the similarity between exterior physical features to infer similarity of product quality or similarity[…]. This does not require confusion between the originator and imitator, or even the belief that the manufacturer is the same". Available studies on the 'initial' effects of copycats offer some support for this contention. These studies indicate that, consumers are unlikely to visually confuse the look-alike and the original brand, however they can readily detect imitation attempt and the associated visual similarity between the private label and the (leading) national brand (Warlop and Alba 2004, Sayman et al 2002), and are influenced by them. As for the size of this influence, the viewpoints are somewhat mixed. Whereas Kapferer (1995) concludes that similarity of packaging leads consumers to believe that manufacturers are identical, Sayman et al. contend that "…this [visual similarity] does not necessarily translate into consumer beliefs that the store brand offers comparable intrinsic quality" (Sayman, Hoch and Raju, 2002, p. 394). Based on a series of experiments, Warlop and Alba (2004) attest that the initial impact of visual similarity on the look-alike brand is generally positive.

While these prior studies provide some interesting insights into the effects of copycatting, they are either survey-based (Sayman et al. 2002; Simonson 1994) or experimental in nature (Barbara Loken et al. 1986; Kapferer 1995; Warlop and Alba 2004; Warlop et al. 2005; Zaichkowsky and Simpson 1996). This leaves us with two important issues. First, while the experimental setup clearly offers its own strengths, it may not fully reflect consumer responses in natural (cluttered) choice settings. Second, the difficulty of integrating successive consumption experiences in experimental or survey settings makes it hard to capture consumer responses based on information processing and learning over time (Foxman et al. 1992). Yet, as indicated by Warlop and Alba (2004), consumer familiarity may be an important mediator of copycat reactions. Consistent with Erdem's (1998) observation that brand knowledge is created over time as consumers learn new experiences, the look-alike strategy may trigger interesting spillovers of consumption experiences between the imitating and the imitator brand which, over time, shape their quality beliefs and brand choice behavior. Especially for frequently purchased consumer packaged goods, this experience-based reaction is expected to be a key performance driver, yet its implications for the imitated and imitating brand remain to be understood.

Our study, therefore, intends to add to the available insights by modeling the dynamic processes of own and cross-quality learning for the copycat and imitated brand, and tracking the ensuing changes in consumer's choices of those brands in real life settings. Before turning to model development and estimation, we discuss the different learning mechanisms and reactions below.

4.2.1 Quality learning from the imitated brand to the copycat.

In many cases, rather than bring about brand confusion, the copycat's objective is to use the look-alike strategy for quality signaling, and to instigate *similarity-quality inferences*. The imitation strategy may then trigger cross-learning from the national brand to the copycat, consumers using consumption experiences with the imitated national brand as signals of the look-alike private label's quality.

Evidence of consumption-based learning among competing brands in a given product category has recently been provided by Janakiraman, Sismeiro and Dutta (2008). Based on the diagnosticity-accessibility framework, these authors argue that spillover effects can occur between direct competitors that do not carry a common brand name, provided that those competitors still bear some form of similarity. In their application (prescription drugs), the similarity stems from physical commonality, drugs functioning in the same pharmaco-dynamic manner and sharing the same side effects. In the case of copycat private labels, the *visual* or trade dress similarity is key. This visual similarity may have diagnostic value: consumers may see the trade dress imitation as a signal on the part of the retailer to communicate quality parity (at a lower price). Rather than being judged deceptive (Campbell and Kirmani 2000), the PL's unique 'status' in the supply chain is bound to lend credibility to the signal of ‘similar quality at a lower price’ – especially for high-equity and powerful retail chains. In such a case, consumption experiences with the original brand would carry over to the imitator brand.

Such cross-learning would produce a dual effect for the copycat. First, it would shift its expected quality level towards that of the imitated national brand. Second, it would remove much of the uncertainty around the copycat’s quality beliefs. Given that prior expectations about a PL’s quality are (slightly) below that of leading national brands (AC Nielsen 2005), but with some uncertainty surrounding it (Batra and Sinha 2000; Erdem et al. 2004), we expect both effects to be positive for the look-alike brand. This is harmful for the imitated brand, to the extent that the copycat becomes more appealing by piggy-backing on it quality, and hence steals away business.

4.2.2 Learning from copycat consumption.

Apart from the initial response to visual similarity described above, consumers’ quality evaluations may evolve as they accumulate consumption experiences with the copycat. Three mechanisms or processes can be distinguished here.

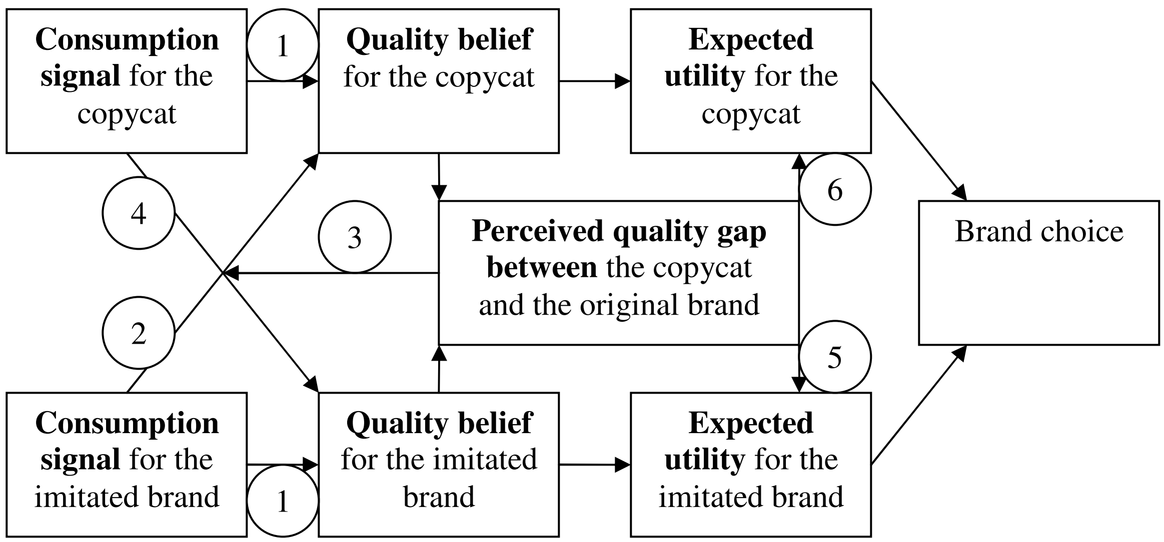
Memory Confusion. A first mechanism refers to the possibility of ‘reverse’ spillover effects from the copycat to the original brand, caused by memory confusion. While the difference in brand names may suffice for consumers to distinguish the original and copycat products when facing the packs, the distinction may ‘fade’ if the two products are no longer physically available. Differently stated, package similarity may cause consumers to mix up the two brands in memory, and wrongfully assign consumption experiences. This memory confusion may impede separate learning about the imitated brand and the copycat (Warlop et al. 2005), and trigger two-way spillovers between the copycat and the imitated brand. In this case, not only is the copycat’s quality belief modeled after that of the national brand, but the national brand’s quality belief gets shaped by consumption experiences with the copycat. Moreover, if the copycat quality is experienced as not far below that of the original, similar ‘reverse’ spillovers may come about as a result of assimilation: the copycat is seen as a good substitute, and the original perceived as less unique as originally thought (Zaichkowsky and Simpson 1996).

Contingent cross-learning. A second interesting phenomenon is that spillovers from the original to the copycat may alter as consumers accumulate information. Based on the diagnosticity-accessibility framework, the degree of spillovers between competing brands is smaller if they are more dissimilar (Janakiraman et al. 2008). Through repeated consumption of the imitator brand, the consumer learns about its true quality and about the quality gap vis-à-vis the imitated national brand (Kapferer 1995). If the quality gap between the original and the copycat is large and consumers become aware of this, we expect cross-learning to dissipate: consumption experiences with the national brand are no longer used as signals of the copycat's quality (see Chapter 3) or vice versa (reduced assimilation, Zaichowsky and Simpson 1996). In a similar vein, memory confusion is bound to dissolve with increased brand experience (Foxman et al 1992).

Reactance and Rewarding Behavior. Third, if the copycat is 'found out' to be substantially inferior to the national brand it imitates, this may produce an additional type of responses on the part of consumers in the form of 'reactance' (towards the imitator) or 'rewarding' behavior (towards the original). Quick and Stevenson (2007) characterize psychological reactance as "an aversive motivational state" that energizes individuals to engage in restoring behavior opposite the threat. Such reactance may be triggered when consumers feel they have been manipulated (Dillard and Shen 2005; Quick and Stephenson 2007). Specifically, in a copycat setting, the package similarity may be interpreted as an intentional ploy to signal quality, and result in negative boomerang effects for the imitator (Campbell and Kirmani 2000). While Warlop and Alba (2004) show that consumers are not likely to "spontaneously penalize brands that blatantly imitate market leaders" (Warlop and Alba, 2004, p. 21), this response may change as they experience the true quality gap: even if the initial signal of same quality was judged believable, consumers may now evaluate it as an attempt to mislead them and for which the retailer needs to be punished. Not only will positive spillovers (enhancement of copycat's quality beliefs) be halted, but the consumer may actually become less attracted to the copycat than would be warranted by its intrinsic quality because of the attempted deception. In case of such reactance behavior, the effect of copycatting will not only be short lived, it will backfire on the imitator. Alternatively, the quality gap may create a positive, 'rewarding' effect for the imitated brand. If the original brand proves to be substantially superior to the copycat private label, this reinforces the notion that it is not easy to imitate, and this aura of 'uniqueness' may further enhance its appeal. Zaichkowsky and Simpson (1996) attribute this to a contrast effect: "Conversely, if consumers have negative experiences with the imitator, then their evaluations of the original and the imitator should be contrasted. Contrasting effects should cause an increase in the evaluations of the original because negative experiences with the imitator may lead to avoidance of the imitator product" (p.32). Note that while reactance to the copycat would benefit all competitors, rewarding effects would only apply to the original brands.

Figure 4.1 summarizes the different mechanisms. In the next section, we propose a Bayesian learning model in which these mechanisms are incorporated.

FIGURE 4.1 CONCEPTUAL FRAMEWORK WITH AN OVERVIEW OF CONSUMPTION-BASED COPYCAT EFFECTS



Note. Arrow 1: within-brand learning; arrow 2: spillovers from the original NB to the copycat PL; arrow 3: ‘conditional learning’, i.e. dependence of the spillovers on the perceived similarity of the both brands; arrow 4: ‘reverse copycat effects’, i.e. spillover from the copycat PL to the imitated NB; arrow 5: ‘rewarding’ effect; arrow 6: ‘reactance’ effect.

4.3 Model Development

4.3.1 Base model without cross-learning.

Our brand choice model builds on existing structural dynamic choice models with consumer brand quality learning and forgetting (Erdem and Keane 1996; Mehta et al. 2004; Narayanan et al. 2005) and very closely resembles the models used in Chapters 2 and 3. It includes cross-brand learning that is contingent on perceived similarity of the involved brands. This contingency is implemented in the same was as in Chapter 3, the difference being that instead of learning among private label brands, here we allow for learning among the imitated national brand and the copycat. Moreover, the model used below extends the specifications in earlier chapters (i) by allowing the extent of cross-brand learning to vary with the direction of the effect (from or to the imitated brand), and (ii) by including 'reactance' and 'rewarding behavior': learned quality deficiencies of the copycat compared to the imitated brand influencing those brands' utility beyond the quality effect itself.

Again, we start by presenting the base model without cross-brand learning (which is similar to that in the previous two chapters), and then discuss how it is extended to accommodate the possible copycat effects.

Like previous learning models, we assume that when choosing from a category assortment, consumers pick the brand that maximizes their (current) utility, which depends on brand quality. As true brand quality is not perfectly known, consumers' choices on different purchase occasions rely on their quality beliefs of different brands at that time. The utility of brand j on purchase occasion t is given by:[15]

$$U_{jt} = f(Q_{jt}) + X_{jt}\beta + \varepsilon_{jt}\,, \qquad [4.1]$$

where Q_{jt} [16]indicates the consumer's quality beliefs about brand j on purchase occasion t, X_{jt} is a vector of utility determinants other than perceived quality observed by both the researcher and the consumer, β are parameters capturing sensitivity to those determinants, and ε_{jt} are i.i.d. extreme value distributed portions of utility unobserved by the researcher but observed by the consumer (for an extensive discussion, see Mehta, Rajiv, and Srinivasan 2004). Like previous researchers (e.g. Crawford and Shum 2005; Narayanan and Manchanda 2009), we assume that consumers exhibit 'constant' risk aversion with respect to their uncertainty about

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[15] We drop the consumer subscript for clarity of exposition.

[16] Table A1 presents an overview of the notation.

the true quality of brands, and capture this by letting quality beliefs enter the utility expression through a negative exponential function:

$$f(Q_{jt}) = -\exp(-rQ_{jt}), \qquad [4.2]$$

where r is a risk aversion coefficient that is greater than 0.

Consumers' quality belief of brand j on purchase occasion t, Q_{jt}, is normally distributed with mean μ_{jt} and variance (or uncertainty) σ_{jt}^2 on occasion t. The consumer then maximizes his or her expected utility which is:

$$E[U_{jt} \mid I_t] = E[f(Q_{jt}) \mid I_t] + X_{jt}\beta + \varepsilon_{jt}, \qquad [4.3]$$

where I_t indicates the consumer's information set in t, in particular, brand quality knowledge obtained through prior consumption. Given the distribution of Q_{jt}, and using [1], we can rewrite this expected utility of brand j on purchase occasion t as (Narayanan et al. 2005):

$$E[U_{jt} \mid I_t] = -\exp\left(-r\left(\mu_{jt} - r\frac{\sigma_{jt}^2}{2}\right)\right) + X_{jt}\beta + \varepsilon_{jt}. \qquad [4.4]$$

Similar to previous learning models, we assume that though consumers do not know brands' true quality, they learn about it through consumption. Each consumption of a brand j in period t – 1, provides a new quality level experience, which we assume to be i.i.d. normally distributed with a mean equal to the true brand quality q_j and variance σ_g^2: $g_{jt} \sim N(q_{jt}, \sigma_g^2)$. The consumer's quality belief of brand j from purchase occasion t – 1, Q_{jt-1}, then gets updated in a Bayesian manner with a series of M_t consumption signals. We summarize this series of unobserved signals g_{jtm} with a mean G_{jt}, which is also i.i.d. normally distributed, $G_{jt} = \frac{\sum_{m=1}^{M_t} g_{jtm}}{M_t} \sim N\left(q_j, \frac{\sigma_g^2}{M_t}\right)$.

While learning gradually reduces consumers' uncertainty, consumers also forget over time, which again increases their uncertainty about brand quality (i.e., σ_{jt}^{2}, see Mehta, Rajiv, and Srinivasan 2004 for a similar approach). In the absence of consumption at t – 1, we expect σ_{jt}^{2} to decay exponentially, $\sigma_{jt}^{2} = \sigma_{jt-1}^{2} * e^{b(w_t - w_{t-1})}$, where b is an estimated decay parameter, and $w_t - w_{t-1}$ refers to the time elapsed between purchase occasions t and t – 1. This leads to the following updating expressions for the mean and variance of brand j's quality belief on purchase occasion t (e.g.Groot 1970):

$$\mu_{jt} = \left(\frac{\mu_{jt-1}}{\sigma_{jt-1}^{2} * e^{b*(w_t - w_{t-1})}} + \frac{d_{jt-1} G_{jt}}{\frac{\sigma_g^2}{M_t}} \right) * \left(\frac{1}{\sigma_{jt-1}^{2} * e^{b*(w_t - w_{t-1})}} + \frac{d_{jt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1} \quad [4.5]$$

and

$$\sigma_{jt}^{2} = \left(\frac{1}{\sigma_{jt-1}^{2} * e^{b*(w_t - w_{t-1})}} + \frac{d_{jt-1}}{\frac{\sigma_g^2}{M_t}} \right)^{-1} \quad [4.6]$$

where on each occasion t, the consumer adopts only one brand, such that $\sum_j d_{jt} = 1$, with d_{jt} = 1 if brand j were chosen at t and 0 otherwise.

4.3.2 Modeling consumption spillovers from the imitated national brand to the copycat

In the above learning model, consumers use the signal from consumption of brand j, g_{jt}, to update their beliefs about brand j only. In the case of a copycat private label, however, we expect consumption experiences with the imitated brand to also be perceived by consumers as quality signals concerning the imitator. While this leaves quality learning for the other brands unchanged, it leads to the following adjusted updating expressions for the copycat's quality beliefs. This formulation is similar to the one proposed in Chapter 3, except that we now make a distinction depending on the direction of learning (from or to the original brand). As already noted in the previous chapter, the formulation is not structural but rather reduced form:

$$\mu_{ct} = (\varphi_c)\left(\frac{\mu_{ct-1}}{\sigma^2_{ct-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ct-1}G_{ct}}{\frac{\sigma^2_g}{M_t}} + \frac{d_{ot-1}G_{kt}}{\frac{\sigma^2_g}{M_t}}\right)\left(\frac{1}{\sigma^2_{ct-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ct-1}}{\frac{\sigma^2_g}{M_t}} + \frac{d_{ot-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1}$$
$$+ (1-\varphi_c)\left(\frac{\mu_{ct-1}}{\sigma^2_{ct-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ct-1}G_{ct}}{\frac{\sigma^2_g}{M_t}}\right)\left(\frac{1}{\sigma^2_{ct-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ct-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1} \quad [4.7]$$

where subscript c refers to the copycat PL brand, o to the original national brand that is imitated, and the weight $\varphi c \in (0,1)$ is an estimated parameter. The variance of quality beliefs on purchase occasion t for the copycat is

$$\sigma_{ct} = (2\varphi_c - \varphi_c^2)\left(\frac{1}{\sigma^2_{ct-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ct-1}}{\frac{\sigma^2_g}{M_t}} + \frac{d_{ot-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1} + (1-\varphi_c)^2\left(\frac{1}{\sigma^2_{ct-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ct-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1} . [4.8]$$

The updating expressions above imply the presence of two types of spillovers from the imitated brand to the copycat. Equation [4.7] indicates that experiences with the original brand influence the *mean quality* belief of the copycat. If the true quality of the copycat is lower that that of the imitated brand, this cross-effect will be beneficial and 'artificially' enhance the copycat's quality belief (of course, the opposite holds if the imitated brand has lower quality than its look-alike). A second imitation effect, captured by Equation [4.8], is that experience transfers from the original brand will reduce the consumer's uncertainty about the copycat's quality. Especially for consumers who have limited experience with the copycat itself, this variance reduction is, again, beneficial. Equations [4.1-4.8] constitute our basic imitation model. As indicated in the conceptual part, several extensions/refinements of this model may be warranted as consumers gain experience with the copycat product. We discuss those extensions below.

4.3.3 Model extensions: memory confusion, contingent cross-learning and experience-based reactance or rewarding.

In addition to the expected spillovers from the original brand to the copycat, actual consumption of the copycat may trigger additional information processing and evaluation mechanisms in the form of memory confusion, contingent cross-learning and experience-based reactance and rewarding. Below, we comment on the specifications used to test for the presence of such mechanisms.

Memory Confusion. If the visual similarity creates confusion in the consumers' memory associations of previous consumption signals, the imitated brand's quality beliefs will, in turn, be shaped by consumption experiences with the copycat. This implies that cross-learning occurs not only from the original to the copycat, but also vice versa, leading to the following adjusted updating expressions for the original brand's quality beliefs:

$$\mu_{ot} = (\varphi_o)\left(\frac{\mu_{ot-1}}{\sigma^2_{ot-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ot-1}G_{ct}}{\frac{\sigma^2_g}{M_t}} + \frac{d_{ct-1}G_{ot}}{\frac{\sigma^2_g}{M_t}}\right)\left(\frac{1}{\sigma^2_{ot-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ot-1}}{\frac{\sigma^2_g}{M_t}} + \frac{d_{ct-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1}$$
$$+ (1-\varphi_o)\left(\frac{\mu_{ct-1}}{\sigma^2_{ot-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ot-1}G_{ct}}{\frac{\sigma^2_g}{M_t}}\right)\left(\frac{1}{\sigma^2_{ot-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ot-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1} \quad [4.9]$$

where, again, subscript c refers to the copycat PL brand and o to the original national brand that is imitated, and where $\varphi_o \in (0,1)$ is a parameter capturing the importance of these reversed spillovers. The variance of quality beliefs on purchase occasion t for the original brand is

$$\sigma_{ot} = (2\varphi_o * - \varphi_o *^2)\left(\frac{1}{\sigma^2_{ot-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ot-1}}{\frac{\sigma^2_g}{M_t}} + \frac{d_{ct-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1} + (1-\varphi_o *)^2\left(\frac{1}{\sigma^2_{ot-1} * e^{b*(w_t - w_{t-1})}} + \frac{d_{ot-1}}{\frac{\sigma^2_g}{M_t}}\right)^{-1}. \quad [4.10]$$

Contingent Cross-Learning. As consumers build up experience with the copycat, they may come to realize that its quality is quite different from that of the imitated product, and refrain from using consumption experiences with the original brand to further update their quality beliefs about the copycat (or vice versa). To capture this phenomenon, we re-specify φc (φo) to reflect consumers' beliefs of the probability that g_{ot} (g_{ct}) is an unbiased signal of the copycat's (original brand's) quality. Specifically, we set[17]:

$$\varphi_u = \eta_u \left(2 * \left(1 - \Phi\left[\frac{|\mu_{ct-1} - \mu_{ot-1}|}{\sqrt{\sigma^2_{ot-1} + \sigma^2_{ct-1}}} \right] \right) \right)^{\kappa_u}, \qquad [4.11]$$

where $u \in \{c,o\}$, Φ refers to the standard normal cumulative density function, and η_u and κ_u are parameters to be estimated (which we call spillover ceiling and spillover contingency parameters, respectively). We restrict them so that $\eta_u \in (0,1)$ and $\kappa \geq 0$. For intuition, note that φ_u can also be written as $\eta_u(1 - \varphi^*_u)^{\kappa u}$, where φ^*_u is the *p*-value in a test of true brand quality differences, given the information set on purchase occasion t.

The lower φ_u, the more likely the consumer is to reject the notion that brands c (the copycat) and o (the original) have the same quality, and the less likely he or she is to use consumption experiences with the original brand to revise his or her beliefs about the copycat. The ceiling parameter η_u captures the probability of cross-brand learning if the consumer believes the look-alike and the imitated brands are of the same quality. The contingency parameter κ_u captures whether and how the probability of cross-brand learning changes as a

[17] Theory only dictates that φ_u should be an increasing function of $|\mu_{ct-1} - \mu_{ot-1}|$ and a decreasing function of $\sigma^2_{ot-1} + \sigma^2_{ct-1}$. The particular choice of a normal distribution cdf, with added flexibility by inclusion of a parameter κ_u, was dictated by parsimony. We also tested a substantially more flexible gamma distribution, but this did not result in an improvement in model fit.

function of the perceived quality similarity of brands c and o. For $\kappa_u \rightarrow 0$, spillovers from the original to the imitated brand are not contingent on perceived brand similarity.

Experience-based Reactance and Rewarding

Consumers who learn the copycat quality to be inferior to that of the imitator brand, may either 'punish' the retailer for this deception, by exhibiting a lower preference for the copycat than would be warranted based on its intrinsic characteristics, or may 'reward' the original national brand, by assigning it a higher utility than would be warranted based on its intrinsic characteristics. We model such behaviors as follows:

$$E[U_{ut} \mid I_t] = -\exp\left(-r\left(\mu_{ut} - r\frac{\sigma_{ut}^2}{2}\right)\right) + X_{ut}\beta + R_{ut} + \varepsilon_{ut} \qquad [4.12]$$

where

$$R_{ut} = (\psi_u)\left(\Phi\left[\frac{\mu_{ot-1} - \mu_{ct-1}}{\sqrt{\sigma_{ot-1}^2 + \sigma_{ct-1}^2}}\right]\right)^{(\tau_u)} \qquad [4.13]$$

where ψ_u and τ_u are estimated parameters (which we call reactance ceiling and reactance contingency parameters, respectively, if u=c; and rewarding ceiling and rewarding contingency parameters, respectively, if u=o). Compared to expression [3], the imitating and imitated brands' expected utility now contains an extra term that reflects the perceived quality gap between both brands. If reactance occurs, we expect the parameter ψ_c to be negative, such that this quality gap produces a further reduction in the look-alike's utility, over and above the direct quality effect in the first term of the expression. On the other hand, if rewarding occurs, we expect ψ_o to be positive, such that the quality gap produces an additional increase in the utility of the original brand. Note that, unlike expression [4.11], Equation [4.13] is affected by the direction of the quality gap, the shape of the function implying that especially positive values of the gap (original quality superior to copycat) produce changes in R_{ut}.

4.3.4 Estimation

Estimation Procedure. The estimation procedure closely resembles the one used in Chapter 2. To accommodate unobserved household heterogeneity, we use a random effects specification, with a normal distribution for the parameters $q_{j,i}$ and β_i and a lognormal distribution (to ensure positive values) for the parameters $\sigma_{g,i}$, b_i, and r_i. We denote the means and standard deviations of $q_{j,i}$ and β_i as ($\nu_{q_j}, \varsigma_{q_j}$) and ($\nu_\beta$, ς_β), respectively. Similarly, the means and standard deviations of the logs of $\sigma_{g,i}$, b_i, and r_i are (ν_{σ_g} , ς_{σ_g}), (ν_b, ς_b), and (ν_r, ς_r), respectively. In addition, σ_0^2 must be homogenous for identification purposes, and we keep φ_u, η_u, κ_u, ψ_u and τ_u homogeneous for the sake of model stability and tractability. Thus, our random effects model contains the listed means and variances as parameters, as well as σ_0^2 , φ_u, η_u, κ_u, ψ_u and τ_u.

To obtain identification, we fix one of the true quality population mean parameters across households (i.e., $\nu_{q_j} = 0$ for j = Private Label 1), the uncertainty regarding brand quality at purchase occasion t = 0 (i.e., $\sigma_0^2 = 1$).

We estimate these parameters using simulated maximum likelihood. The Technical Appendix provides details pertaining to the log likelihood and model estimation procedure (similar to Mehta, Rajiv, and Srinivasan 2004).

4.4 Empirical Analysis

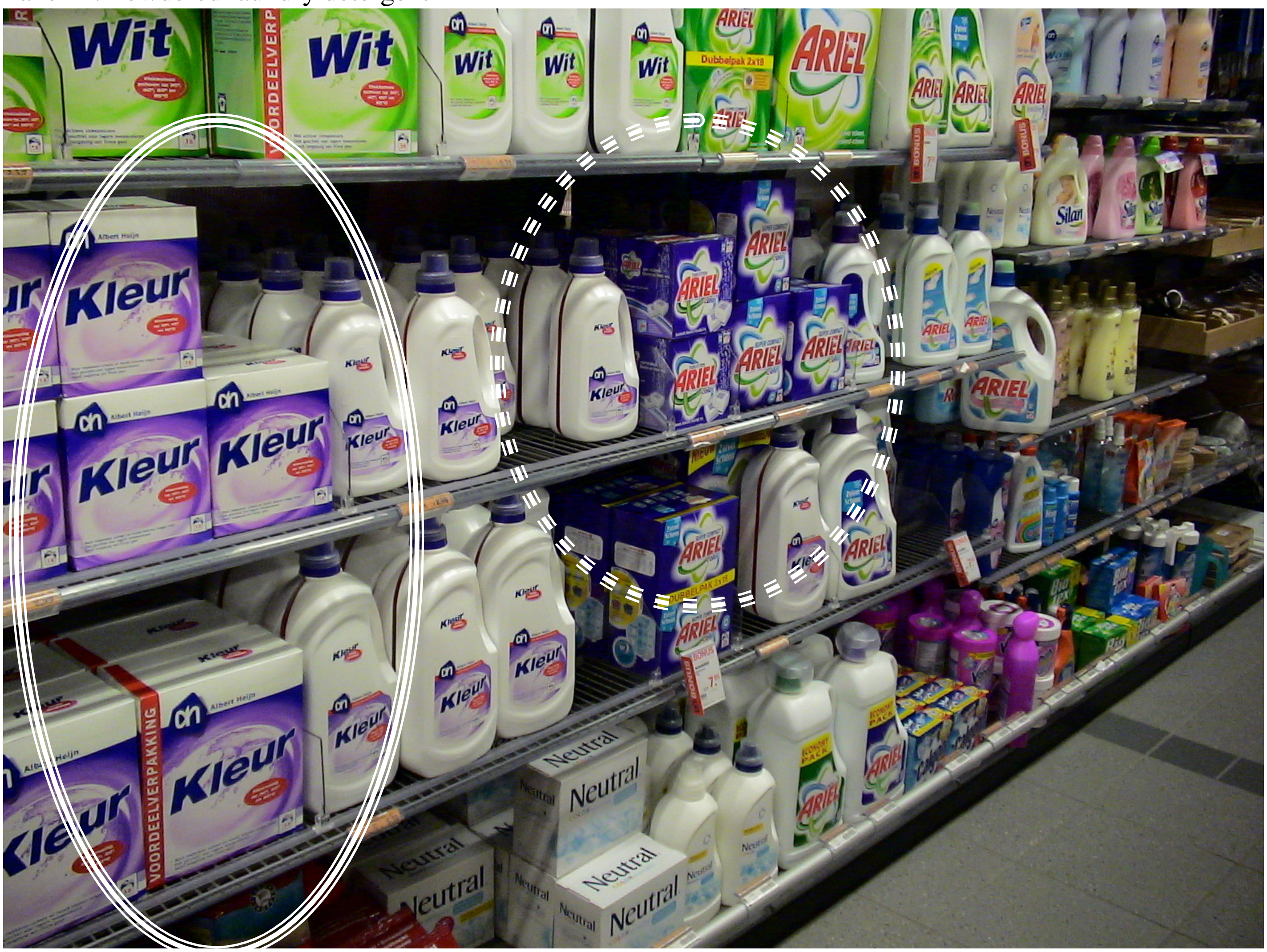
4.4.1 Data and setting

We estimate our models on scanner panel data for two cases. The first case uses data from the powdered laundry detergent category at the leading retail chain in the Netherlands. The second case refers to the liquid dish detergent category, in a major competitive Dutch chain. In both settings, the retailer's (own-name) private label imitates the leading national brand in that category, by adopting a package whose shape, color and pictorials clearly mimic those of (but are not identical to) the original.

Figure 4.2 provides pictorials of the packages for the copycat, the imitated brand, and competitors. Note that, in each category, the copycat's private label name clearly appears on the package, which further reduces the likelihood of in-store visual confusion (consumers mistakenly picking up the copy instead of the original national brand).

FIGURE 4.2 PACKAGES OF BRANDS USED IN THE STUDY

Panel A. Powdered laundry detergent



Panel B. Liquid dish detergent

Note. Original National Brands indicated with dashed line and copycat Private Labels with solid line.

In our estimation sample, we include the top three brands in each category (for similar approaches see Chen and Yang 2007; Dekimpe et al. 1999; Nijs et al. 2007), including the copycat private label and imitated national brand, which account for 61% and 81% of category purchases in powdered laundry detergent category and liquid dish detergent category respectively. Table 4.1 presents basic descriptive statistics of the sample brands. While in the powdered laundry detergent category the leading national brand has the largest share of purchases, for liquid dish detergents it is the private label that accounts for the highest purchase share. This may be related with the much lower price of the copycat PL in the latter category: while in both categories private labels are the least expensive of the three brands, the price gap between the copycat PL and original NB is more than twice as large in the liquid dish detergent category (32% vs. 13%). Our data set contains information on weekly shopping trips and purchase histories for households, as well as prices, display and feature activities for each brand. In total, powdered laundry detergent category (liquid dish detergent category) data comprise 1166 (2008) purchase records from 287 (443) households, which are randomly split into an estimation sample of 899 (1593) and a holdout sample of 267 (415) observations.

TABLE 4.1 BASIC DESCRIPTIVE STATISTICS OF THE SAMPLE BRANDS

	Share of sample purchases	**Number of sample purchases**	**Average price per volume unit**	**Share of households never buying a brand during promotion**
Powdered laundry detergent category		1166		
Imitated national brand (ARIEL)	0.43	502	0.42	0.029
Copycat private label (ALBERT HEIJN)	0.39	458	0.36	0.186
Secondary national brand (OMO)	0.18	206	0.47	0.102
Liquid dish detergent category		2008		
Imitated national brand (DREFT)	0.34	685	0.33	0.176
Copycat (Private label T.S.N.)	0.52	1051	0.22	0.444
Secondary national brand (DUBRO)	0.14	272	0.25	0.260

Since our focal question is how the consumption experiences of the original brand, shape consumers' subsequent quality beliefs about the copycat PL and their brand choices, the key property of our data (which will allow us to identify such effects) is whether we observe consumers who purchase each of the brands involved. Our sample features 442 households in the liquid dish detergent category (286 in the powdered laundry detergent category), of whom 245 (171) exclusively buy the original brand, 261 (97) exclusively buy the copycat PL brand,

and 98 (31) households buy both brands. Moreover, since the learning process is about dynamics, another important data feature is within household, over time variation in brand choices. To get a feel for this, we divide the data into four 32 week-periods, and compute the choice shares for the original brand and the copycat per household and period. Next, we calculate the standard deviation of those shares per household. Table 4.2 summarizes these figures, averaged across households, and reveals that – indeed – brand purchase shares do vary within households across the subsequent periods, for the original brand as well as the copycat.

TABLE 4.2: WITHIN-HOUSEHOLD VARIATION IN PURCHASE SHARE OF THE ORIGINAL BRAND AND THE COPYCAT BRAND OVER TIME

Brand	**Number of households**	**Brand purchase share**	
		Average	**Within-household standard deviation**
Liquid dish detergent category			
Original brand	245	.41	.1138
Copycat	261	.46	.1075
Powdered laundry detergent category			
Original brand	171	0.5073	0.0765
Copycat	97	0.2652	0.0711

[a] Calculations in this table only include households who bought the brand at least once in 32-week sub period.

[b] Standard deviation of the household's PL share in the chain, calculated over four 32-week sub periods, and then averaged over households visiting the chain.

As 18.6% in the Powdered laundry detergent category (44.4% in the Liquid dish detergent category) of households never buy the PL during promotion as well as non-promotional conditions, these over-time changes cannot be entirely attributed to the brand being on deal. One way to pin down possible copycat effects without estimating a model is by focusing on consumers for whom the copycat PL is likely to be a new brand, i.e. who did not buy the copycat PL brand during the first 32 weeks of the data. We median-split those consumers into heavy and non-heavy buyers of the imitated brand, keeping in mind that households who consume the original brand during this first period, may use these experiences to learn about the copycat. We then compare the purchase share of the copycat PL in the subsequent period following the households' first observed copycat consumption, for these two subgroups (heavy and non-heavy buyers of the imitated brand). In each product category, it appears that those households who were heavy users of the original brand, have significantly higher choice share of the copycat PL in the subsequent period ($p<.05$) for Liquid dish detergent category, $p<.01$ for Powdered laundry detergent category), which is at least consistent with our expected cross-brand spillovers.

4.4.2 Estimation Results

Fit and predictive validity compared with benchmark models.

Table 4.3 provides an overview of the estimated models' descriptive and predictive validity. In both categories, the model with contingent cross-brand learning ($M_{o\rightarrow c|ConL}$) outperforms the models with no learning (M_1), within brand learning (M_2), and cross-brand learning from the original to the copycat ($M_{o\rightarrow c}$), yielding improved in-sample log-likelihood and AIC measures, and higher out-of-sample log-likelihood levels. Further model extensions, e.g. including - next to contingent cross-brand learning - either reverse effects ($M_{o\leftrightarrow c}$), or reactance ($M_{o\rightarrow c|Reac}$), do not result in improvements in model fit or predictive validity. Evidence for rewarding effects is somewhat ambiguous. While the incorporation of rewarding behavior (model $M_{o\rightarrow c|Rew}$) does not improve holdout sample performance for dish detergents, it does lead to a slightly improved in-sample log-likelihood and superior predictions in the powdered laundry detergent category – attesting that positive feedback towards the imitated brand cannot be excluded in that category.

TABLE 4.3 OVERVIEW OF ESTIMATION RESULTS –GOODNESS OF FIT AND PREDICTIVE VALIDITY

	Log-likelihood, estimation sample	Log-likelihood, holdout sample	AIC, estimation sample
PANEL A Powdered laundry detergent category			
No learning	-244.8804	-56.723	519.7609
Within-brand learning only	-206.6074	-53.7891	451.2149
Cross-brand learning	-205.3424	-53.4627	452.6847
Cross-brand learning with contingency	-204.1361	-53.1143	446.2722
Cross-brand learning with contingency and reverse effects	-204.1182	-53.1089	454.2365
Cross-brand learning with contingency and reactance	-204.1143	-53.1249	456.2285
Cross-brand learning with contingency and admiration	-203.3756	-51.9701	452.7512
Cross-brand learning with contingency from non-imitated national brand (robustness check)	-205.8115	-53.504	545.3403
PANEL B Liquid dish detergent category			
No learning	-505.4567	-154.4277	1040.9134
Within-brand learning only	-437.1682	-150.8885	912.3364
Cross-brand learning	-437.0653	-150.4227	916.1305
Cross-brand learning with contingency	-431.3283	-146.5695	904.6565
Cross-brand learning with contingency and reverse effects	-431.0307	-146.4945	908.0614
Cross-brand learning with contingency and reactance	-426.2376	-154.5683	898.4751
Cross-brand learning with contingency and admiration	-428.9651	-148.9072	903.9301
Cross-brand learning with contingency from non-imitated national brand (robustness check)	-435.984	-151.1869	913.968

Notes: The underlined outcome indicates the best fitting model for each category.

Taken together, these results support the presence of significant spillover effects from the imitated brand to the copycat. Second, they suggest that there is a limit to these effects: allowing for reduced learning as consumers become aware of the quality gap. So, whereas the copycat initially enjoys positive quality spillovers from the original brand, these spillovers gradually decline if low-quality copycat experiences accumulate. Third, the results indicate that the quality spillovers are unidirectional, including only consumption-based quality learning from the copycat to the original brand. Memory confusion, therefore, does not seem prevalent, and the original brand's quality beliefs are not affected by copycat experiences. These patterns are similar for powdered laundry detergent as well as liquid dish detergents. What is different between categories, finally, is the rewarding effect. For powdered laundry detergent, the original brand's utility is enhanced if the consumer becomes aware of the quality gap with the private label. In the liquid dish detergent category, such a rewarding effect does not seem to prevail. A tentative explanation is that, in settings where the original national brand charges a premium price and the price gap with the copycat is substantial (as is the case for liquid dish detergents), quality superiority of that national brand is not considered something that the brand needs to be particularly 'commended' or rewarded for .

To further ascertain that the consumption experience spillovers from the national brand to the private label stem from their visual similarity, we estimated – as a robustness check – an alternative model in which we allow the private label to receive spillovers from a leading non-imitated national brand. As expected, for each category-retailer combination, this model does only as good as the model without cross-learning in descriptive and predictive terms, and worse than the model with spillovers from the imitated original.

4.4.3 Parameter estimates.

Table 4.4 reports the parameter estimates for the best fitting model for each retailer and category. Overall, the parameters clearly have face validity. For both samples, the effects of display, feature, and display plus feature, are significant and positive, while the price sensitivity parameters are significantly negative. In both categories, the copycat private labels exhibit a lower mean estimate of the true quality distribution in the population. Yet, they are also characterized by a higher standard deviation for the mixing distribution, suggesting that households are relatively heterogeneous in terms of their preferences for private labels.

TABLE 4.4 PARAMETER ESTIMATES FOR THE BEST FITTING MODEL

Panel A: Powdered laundry detergent category						
	Mean Across Households			Standard Deviation Across Households		
	Symbol	Parameter Estimate	S.E.	Symbol	Parameter Estimate	S.E.
True Brand Quality						
Imitated National Brand	ν_{q_1}	1.04	0.401	ς_{q_1}	0.12	0.032
Copycat Private Label	ν_{q_2}	1	Fixed	ς_{q_2}	0.20	0.094
Secondary National Brand	ν_{q_3}	1.05	0.202	ς_{q_3}	0.09	0.157
Other Determinants of Utility						
Feature and display	$\nu_{\beta_{FD}}$	4.08	1.072	$\varsigma_{\beta_{FD}}$	0.10	0.128
Feature only	$\nu_{\beta_{FO}}$	0.25	.031	$\varsigma_{\beta_{Fo}}$	0.14	0.253
Display only	$\nu_{\beta_{DO}}$	3.42	.529	$\varsigma_{\beta_{DO}}$	1.81	0.929
Price	ν_{β_P}	-0.24	.194	ς_{β_P}	0.98	0.724
Learning and Forgetting						
Log of standard error of consumption signal	ν_{σ_g}	0.34	0.228	ς_{σ_g}	0.31	0.330
Log of forgetting parameter b	ν_b	-4.98	.823	ς_b	0.07	10.872
Log of risk aversion parameter	ν_r	0.46	0.134	ς_r	0.47	0.367
Transformed spillover ceiling parameter	log(1/(ηc - 1))	0.84	0.927			
Log of spillover contingency parameter	log(κuc	4.07	1.041			
Log of rewarding contingency parameter	log(τuo	2.44	1.032			
Rewarding ceiling parameter	ψo	3.38	2.239			
Variance of quality belief at t = 0	ν_0	1	fixed			

Panel B: Liquid dish detergent category						
	Mean Across Households			Standard Deviation Across Households		
	Symbol	Parameter Estimate	S.E.	Symbol	Parameter Estimate	S.E.
True Brand Quality						
Imitated National Brand	ν_{q_1}	1	fixed	ς_{q_1}	.68	.034
Copycat Private Label	ν_{q_2}	.96	.185	ς_{q_2}	.35	.087
Secondary National Brand	ν_{q_3}	.76	.252	ς_{q_3}	.09	.564
Other Determinants of Utility						
Feature and display	$\nu_{\beta_{FD}}$	11.58	2.835	$\varsigma_{\beta_{FD}}$	2.73	.554
Feature only	$\nu_{\beta_{FO}}$	2.52	.971	$\varsigma_{\beta_{Fo}}$	.68	.830
Display only	$\nu_{\beta_{DO}}$	1.63	.819	$\varsigma_{\beta_{DO}}$	.52	3.276
Price	ν_{β_P}	-1.21	.549	ς_{β_P}	.84	.932
Learning and Forgetting						
Log of standard error of consumption signal	ν_{σ_g}	.78	.279	ς_{σ_g}	.12	1.317
Log of forgetting parameter b	ν_b	-5.05	1.492	ς_b	.81	.474
Log of risk aversion parameter	ν_r	.08	.182	ς_r	.48	.816
Transformed spillover ceiling parameter	log(1/(ηc - 1))	.83	.578			
Log of spillover contingency parameter	log(κc)	4.09	1.297			
Variance of quality belief at t = 0	ν_0	1	fixed			

The risk aversion, consumption-based learning, and forgetting parameters are also in line with earlier findings from the literature (e.g. Crawford and Shum 2005; Erdem and Keane 1996). As expected, risk aversion is higher for powdered laundry detergent than for liquid dish detergents, implying stronger uncertainty avoidance in this category. It is interesting to observe that the standard deviation of the consumption signal is lower for powdered laundry detergent than for liquid dish detergents, suggesting that individual consumption signals are more informative in the former category. At the same time, the standard deviation of this parameter across the population is higher, indicating that consumers are more heterogeneous in terms of how much they learn from a consumption experience as compared with the liquid dish detergent category. Next, our findings imply that, on average, consumers forget half of the knowledge gained through a single consumption within 16.15 weeks (powdered laundry detergent) and 16.34 weeks (liquid dish detergents), figures comparable to those reported by Mehta, Rajiv, and Srinivasan (2004) (19.8 weeks) and in Chapters 2 and 3.

Of key interest to us are the parameters related to cross-effects between the original brand and the copycat. Based on the findings in Table 4.3, we retain two sets of estimates here. First, we have the parameters η_c and κ_c, capturing the consumption experience spillovers from the national brand to the copycat (see Equation [4.11], with u=c). The transformed estimates of the ceiling parameter, $\ln(1/\eta_c -1)$, amount to . 83 and .85 for powdered laundry detergent and liquid dish detergent category respectively, implying that when the imitating PL and imitated NB are of the same quality, about 70% of the consumption signal from the imitated NB is used to update the belief of the imitating PL. Transformed estimates for the parameter κ_c, which reflects how strongly quality differences between the original and the copycat reduce cross-learning, are also similar in both categories ($\ln(\kappa_c)$= 4.06 and 4.09 for powdered laundry detergent and liquid dish detergents, respectively). These parameter values imply that in the absence of prior brand experience, cross effects would still occur up to a quality difference of .25. However, this figure rapidly drops as the consumer's knowledge about the quality gap becomes more precise: after 10 consecutive brand purchases, spillovers virtually disappear with a quality gap of .12 between the original and the copycat. These figures should be considered relative to the difference between the (population mean) true quality of the copycat and the original brands in our sample (which is about .05), and the standard deviation of true brand quality in the sample (which ranges between .05 and .21).

A second set of estimates relates to the 'rewarding' effect (parameters (ψ_o) and (τ_o) in Equation [4.13]), which only improves predictions in the powdered laundry detergent category. The parameter (ψ_o) has the expected positive sign, suggesting that a large quality advantage of the original over the copycat entails an extra utility 'reward' for the former. The parameter (τ_o) is such that the effect is strongly contingent on consumers' experience, as will be illustrated in the next section.

4.4.4 Implications for choice shares

The results so far indicate that, while some copycatting effects seem absent (i.e. memory confusion and reactance), others are at work (i.e. contingent cross-learning from the original to the copycat in both categories, and rewarding behavior in the powdered laundry detergent group). The key question remains, however, how the identified effects influence the choice shares of the imitated brand and the copycat over time, and, in case 'rewarding' behavior takes place, whether the retailer's imitation strategy is ultimately beneficial ('friend') or harmful ('foe') to the original national brand. Moreover, from a managerial perspective, it is interesting to gauge how this impact depends on the brands' relative positioning among consumers.

Given the complex, non-linear structure of the model, we need to conduct simulations to illustrate the strategic implications and the economic significance of the findings. Below, we use such a simulation approach. The results are plotted in Figures 4.3, 4.4 and 4.5. We investigate how brands' choice shares are impacted by (i) consumption based learning from the original to the copycat on brand choice shares (Figure 4.3) and, (ii) for the powdered laundry detergent category, rewarding behavior (Figure 4.4), as well as (iii) the total (net) effect of cross-learning from consumption and rewarding (Figure 4.5). We consider how this effect evolves over time (z-axis) and depending on relative positioning of the copycat PL and original NB (x-axis). To obtain these results, we simulate 1000 purchase histories, composed of 200 choices among the copycat PL, the imitated brand, and the non-imitated national brand. The relative quality of the copycat PL vs. the original varies from -.5: copycat inferior, to +.5: copycat superior. For each purchase history, we draw a parameter set from the estimated parameter distributions in Table 4.4, panels A and B. We do this for a number of settings. First, we 'turn off' both the spillover effects to the copycat (by using updating equations [4.5] and [4.6] for all brands) and the rewarding effects (by using utility expression 3 for all brands). Then, we 'turn on' the spillover effects to the copycat (by using learning Equations [4.7], [4.8] and [4.11] for the original NB and copycat PL). Finally, we 'turn on' the rewarding effects (using utility expression 13 for the original NB and the copycat PL). For each of these settings, we compute the corresponding choice shares of the three brands, and then look at the share differences.

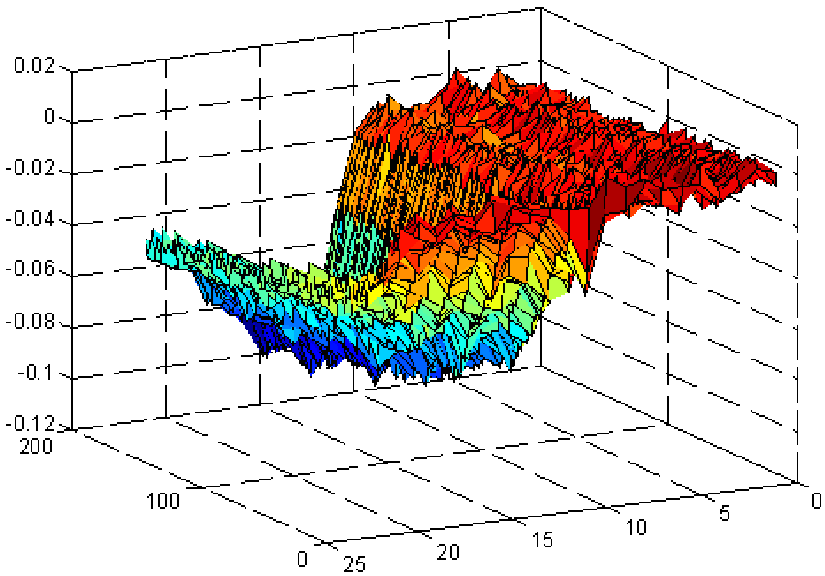
Figure 4.3, Panel A, pictures the effect of cross-brand spillovers on the copycat private label, Powdered laundry detergent[18]. The figure shows that the copycat PL share gain from cross-learning can become quite sizable, that is, up to 10 percentage points of choice share can be transferred from the imitated NB to the copycat. As expected, the effect exists almost exclusively when PLs are worse than NBs. Interestingly, provided that the PL is of lower quality than the NB, the effect is very weakly sensitive to the size of the quality gap. About 50% of the effect is still present when the gap between the PL and the NB is 10 times larger than the gap we observe in our sample. This casts doubt on whether the imitated national brands can prevent spillovers by increasing their quality.

When the imitated NB has lower quality than the copycat, the impact of cross-brand learning on the PL remains close to zero. Apparently, the negative impact of spillovers on the copycat's mean quality belief (experience with a lower quality original NB would lead to an underestimation of the true copycat quality), is compensated by the positive effect of reduced uncertainty. This finding suggests that top-quality PLs do not benefit from a copycat strategy.

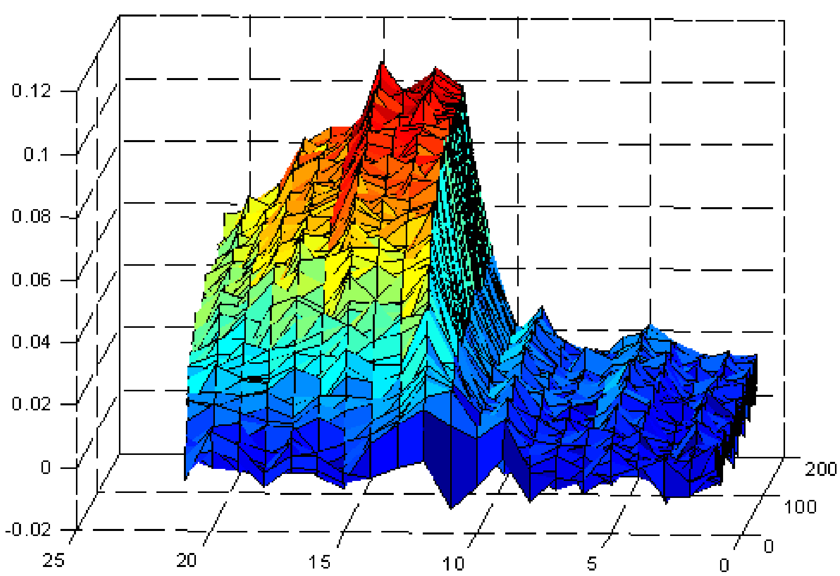
[18] Results for liquid dish detergents are qualitatively similar.

FIGURE 4.3 IMPACT OF CONSUMPTION SPILLOVERS FROM THE IMITATED BRAND TO THE COPYCAT

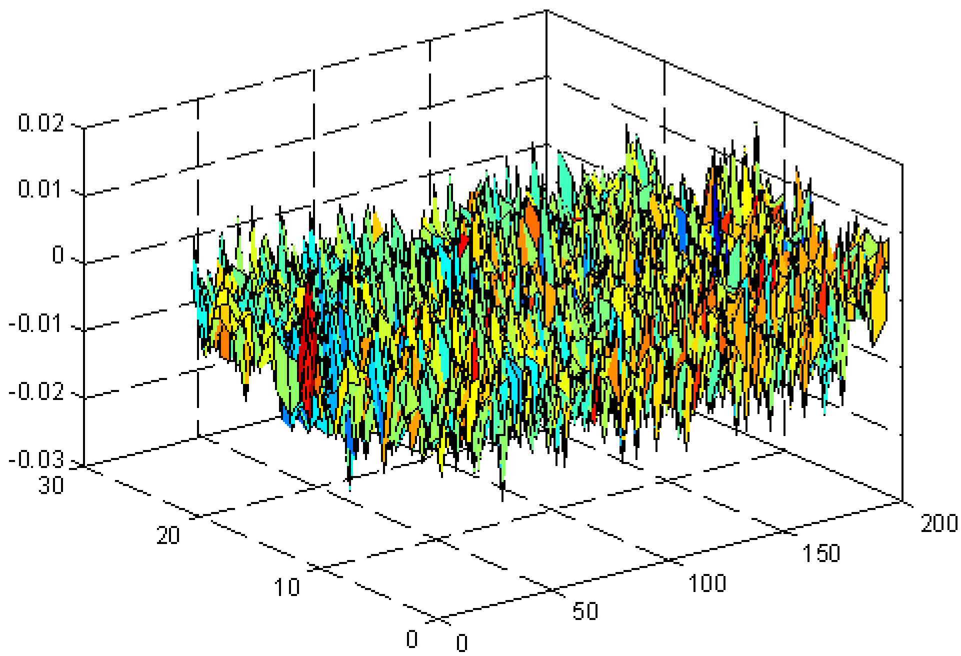
Panel A. Impact on the imitated NB's choice share



Panel B. Impact on the copycat PL's choice share



Panel C. Impact on the non-imitated NB's choice share



Note: Y- axis: market share gained by the PL through copycatting;
X-axis (with scale 0-25): similarity of NB and PL, for values 0-12.5 PL is higher quality;
Z-axis (with scale 0-200): 5- week periods at the end of which we simulate brand choices.

An interesting pattern emerges when we also consider the impact of accumulated experience (Z-axis). As expected, the share gain from cross-learning grows over time as consumers learn about the original NB and copycat PL, but especially so if the true quality gap between both brands remains modest. In both analyzed categories, the effect of copycatting on market share takes place gradually over time[19]. It reaches about 90% of its potential in about 100 purchase cycles. This implies that the effects of copycatting are likely to be long lived, and difficult to spot or pin down in real life. For the quality gap observed in our samples (.04

[19] When brands have the same quality, the effect takes place faster, e.g. 80% of it already occurs after the first purchase.

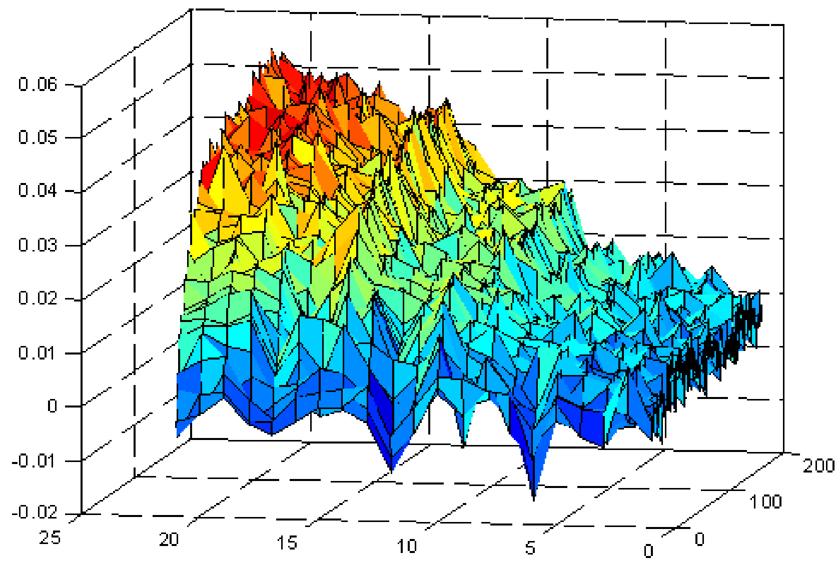
and .05), after 20 purchases, the imitating PL enjoys a market share gain of 3.2% in the powdered laundry detergent category, and of 1.1% in the liquid dish detergent category, attributable to reputation spillovers from the imitated national brands.

Figure 4.3, Panel B and C, show how the cross-brand spillovers enhance or reduce the choice shares of the imitated brand, and the non-imitated competitor, respectively. In each category, we find that the market share of the private label is mostly appropriated from the imitated NB, whereas the secondary NB appears to be unaffected. This may seem counterintuitive at first sight, given that we do not observe reverse spillover effects from the copycat PL to the imitated NB, but only spillovers from the NB to the copycat PL. The reason for the observed substitution pattern is that the positive spillover effects to the copycat only arise from consumption experiences with the original brand and, hence, (are stronger) among consumers who (frequently) chose those brands in the first place.

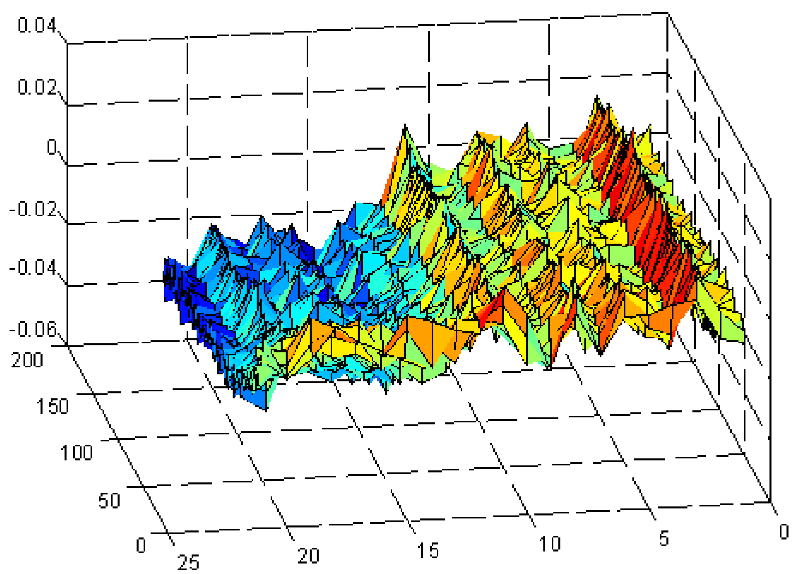
Figure 4.4 pictures the additional impact of rewarding behavior on brand choice shares, a response only observed for powdered laundry detergent. As can be seen from Panels A, B and C of the figure, rewarding behavior influences the choice shares of all three brands: it produces an upward shift for the imitated NB, and a loss for the other two brands. The effect becomes more pronounced (i) as the NB becomes better than the PL and (ii) over time, as consumers become more aware of this quality superiority. The maximum effect within the simulated region is a 5 percentage point gain by the imitated NB, corresponding to a 2%-3% loss for both the copycat PL and the non-imitated NB.

FIGURE 4.4 IMPACT OF REWARDING BEHAVIOR

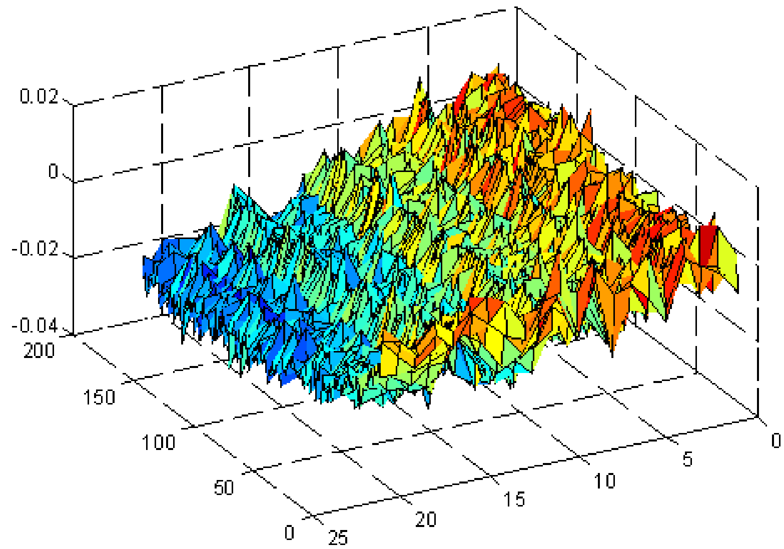
Panel A. Impact on the imitated NB's choice share



Panel B. Impact on the copycat PL's choice share



Panel C. Impact on the non-imitated NB's choice share

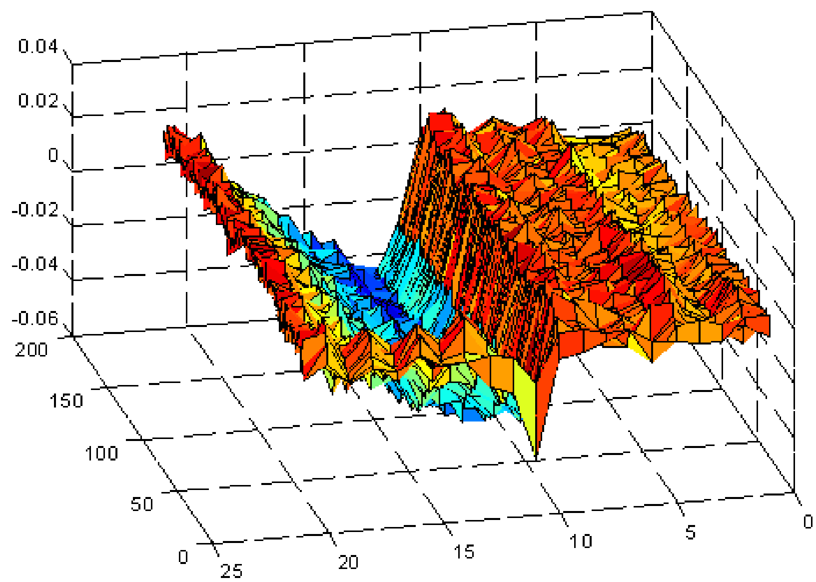


Note: Y- axis: market share gained by the PL through copycatting;
X-axis (with scale 0-25): similarity of NB and PL, for values 0-12.5 PL is higher quality;
Z-axis (with scale 0-200): 5- week periods at the end of which we simulate brand choices.

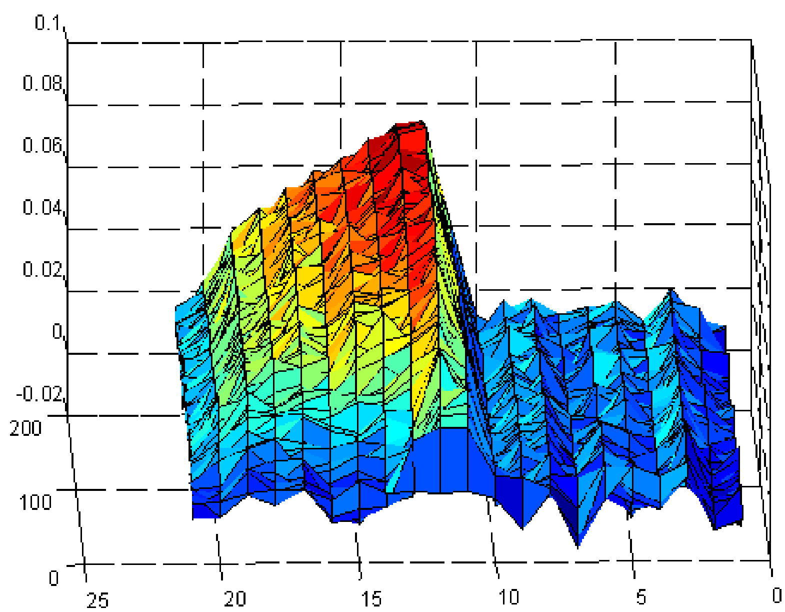
Figure 4.5, finally, indicates the total effect of cross-brand spillovers and rewarding behavior in the powdered laundry detergent category. Again, we find effects for all three brands. The figure shows that, even in the presence of positive rewarding behavior, the impact of copycatting is the most negative for the imitated NB, somewhat negative for the non-imitated NB, and positive for the PL (max 10 percentage points of the choice share). Yet, the pattern of the effect is now clearly shaped by quality differences. The choice share gain by the imitating PL is obtained only when the PL is better than the imitated NB, it grows gradually over time, and decreases to virtually zero as the NB becomes much better (10 times the observed difference in quality).

FIGURE 4.5 COMBINED CROSS-BRAND SPILLOVERS AND REWARDING EFFECT (POWDERED LAUNDRY DETERGENT)

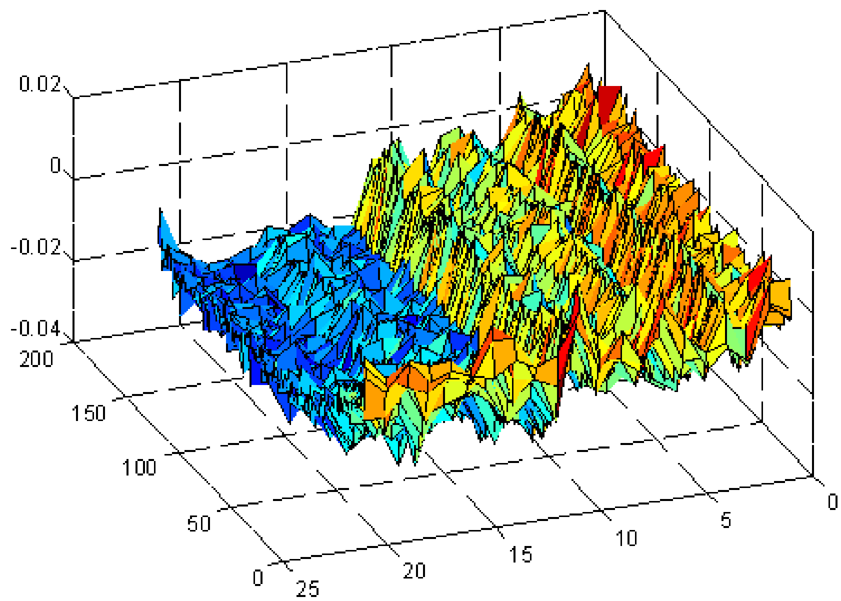
Panel A. Impact on the imitated NB's choice share



Panel B. Impact on the copycat PL's choice share



Panel C. Impact on the non-imitated NB's choice share



4.5 Conclusions, limitations and future research

4.5.1 Conclusions

Copycat effects. To the best of our knowledge, our study is the first to analyze private label copycat effects through consumption-based learning in a real life setting. We develop a brand choice model that accommodates dynamic cross-brand learning among the imitated national brand and the private label copycat, and calibrate it on household panel scanner data sets from two product categories in two retail chains. Our results yield several interesting insights on how copycatting affects the leading national brand, as well as its look-alike and competitors.

First, we find clear evidence of imitation effects in the form of consumption-based learning from the original to the copycat. Not only is this effect statistically significant, it may also be sizeable. In case the copycat PL has lower quality than the NB, the effect is clearly positive. The copycat benefits from the look-alike strategy, as the consumption experiences with the imitated national brand not only make it seem more familiar (less quality uncertainty) but also of higher quality. This leads to an upward shift in the choice share of the copycat, at the expense of the imitated brand. Moreover, the effect is only weakly dependent on the quality gap between the imitator and the original brand, and it builds up gradually with experience.

In contrast, if the copycat quality exceeds that of the original, it seems to have little to gain from the imitation strategy. In this case, the positive familiarity spillovers from the original brand (which reduce initial uncertainty concerning the imitator's quality offer) cancel out against the negative quality belief bias generated by the original (whose quality would be worse and thus lead to an underestimation of the copycat's quality). It seems that, under these circumstances, the copycat practice is not particularly helpful to the imitator, nor harmful to the imitated.

Second, we do not observe any confusion effects: the original brand's average quality beliefs are not jeopardized by the copycat, irrespective of whether the latter's quality is worse or not. This suggests that, notwithstanding the physical similarity, mentioning major retailer's PL brand name on pack not only prevents initial visual confusion (as indicated by Warlop and Alba 2004), but also prevents consumers from mixing up consumption experiences in memory, especially in cases where the visual similarity is clear but not exact.

Third, we obtain some partial indications for rewarding behavior: consumers who experience the original to be superior over the copycat developing an extra positive attitude towards the original in the powdered laundry detergent category. This response shifts the choice share of the imitated brand slightly back upward, to the detriment of both the copycat and the non-imitated competitor. However, we only observe such rewarding behavior in the powdered laundry detergent (not the liquid dish detergent) category. A tentative explanation is that this rewarding response only appears when the price gap is small, in which case consumers can be expected to believe the original deserves to be commended for its high quality offer.

Fourth, we do not observe any reactance on the part of consumers, even after they find out the true (lower) quality of the copycat. This may be because reactance is too weak an effect to show up in a real life setting, or because it does not exist in our particular data set. Regarding the latter point, in our sample, the PL name is clearly indicated on the package such that retailers cannot really be accused of trying to lure consumers into picking up the wrong pack. Also, our copycat PLs are cheaper and, in the eyes of the 'average' consumer, not much worse than the imitated NBs. Therefore, the quality gaps relative to the price gaps may have been insufficient to trigger reactance among panel members. We note, however, that our two settings fall within the typical copycat price and quality description given by Kumar and Steenkamp (2007), suggesting that our observed effects may apply for many commonly observed copycat situations.

Apart from shedding light on the separate mechanisms, our results also document the combined effect of copycatting over time. We find that, even though the lower quality copycat does have some 'friendly' features for the original brand in the form of rewarding behavior, the typical net effect is that of a 'foe': the imitation strategy generating extra choice share for the PL imitator, mostly at the expense of the original brand. Only if the leading brand offers by far superior quality at a price not too high compared to the imitator, do we find the imitation effect to die down.

Managerial implications. Our findings have several implications for managers. From the retailer's perspective, we provide real-life evidence for the overarching message that copycatting pays off. Interestingly, our results suggest that, when pursuing a look-alike strategy, there is not much to gain from offering improved quality over the original. Instead, it seems that such an approach would actually cause the potential benefits of copycatting to dilute. Clearly, this is a tentative and challenging finding that needs further verification. It does, however, corroborate Kumar and Steenkamp (2007)'s observation that retailers aiming to establish a premium quality position should not combine this with an imitation strategy. The advantages of copycatting become most visible if the imitating PL's quality is below that of the leading national brand. It also appears that even larger gaps are fine, it may be that this holds only as long as there is a sufficient price differential with the leading brand to justify this difference and avoid rewarding behavior towards the original NB.

For leading manufacturers, the ‘mirror’ message is twofold. First, private labels with quality clearly superior to that of the national brand, do not seem to become more of a ‘foe’ by adopting a copycat approach. A tentative conclusion is that, for those private labels, there seems to be little point in ‘forcing’ them to abandon the imitation strategy. Second, the findings are quite different for the more common lower quality copycats. Even though these copycats may exhibit some ‘friendly’ features in the form of rewarding effects, the overall impact of their imitation strategy seems particularly detrimental to the imitated brand. Even in the absence of visual confusion, such copycats may hurt the original’s market share more than that of non-imitated competitors, and especially steal away its regular brand buyers with higher than average quality beliefs. However, given that the effect is observed with non-exact trade dress imitation (and, hence, low likelihood of visual brand confusion), litigation is unlikely to be a successful defense strategy. Striving for superior quality does not seem to be a ‘sure cure’ either: while our model suggests that spillovers diminish as the NB-copycat PL quality gap increases, the feasibility of this strategy is doubtful given how large the quality gap would need to be for spillovers to disappear, or rewarding behavior to take over. Our findings, therefore, are in line with the claim that the NB’s window of opportunity lies in continued innovation in product features and packaging (Kumar and Steenkamp 2007), reaping the benefits of innovation successes before established retailers’ copycats have truly ‘settled in’.

Last but not least, our study may have relevance for policy makers. The typical focus in litigation, and criterion to rule against copycats, was the presence of immediate visual confusion. Our study empirically confirms earlier statements by, e.g., Collins-Dodd and Zaichowsky (1999) and Warlop and Alba (2004) that copycats’ harmful effect for the original brand may well extend beyond such visual confusion. Our results also suggest that the effect gradually evolves - so that the full copycat impact may only become apparent over time. While this makes the copycat implications difficult to pin down without longitudinal data, we also indicate conditions under which these effects are more likely to pertain and that may serve as guidelines for policy refinements.

4.5.2 Limitations and Directions for Future research.

While our study provides real life evidence on the prevalence of cross-learning effects towards copycats, it also raises several interesting issues that need further study. For one, our findings suggest that the amount of spillovers and the effect of rewarding behavior depends on the quality of the copycat vis-à-vis the imitated brand. Even though this observed pattern makes intuitive sense and is in line with prior expectations, it would be interesting to confirm the effect of the quality gap in other settings, where quality differences not only arise among heterogeneous consumers, but also across a range of imitator-imitated brand pairs. Also, we found evidence of rewarding behavior only in settings where superior quality evaluations of the original brand went along with only a modest price premium. Yet, this effect of price positioning in interaction with copycat spillovers and rewarding behavior certainly needs further investigation.

Second, even though we already observe the imitation strategy to be predominantly harmful to the original brand, we do not claim to have captured its full effect, and expect our estimates to be only conservative. For instance, the look-alike strategy may increase the likelihood of PL inclusion in the consideration set when it first enters the market. Proper assessment of that effect would call for the analysis of a broad set of private label introductions, some with and some without a copycat strategy – an approach calling for different data and models than ours. Also, our analysis is confined to quality belief and brand choice effects. Yet, as indicated by Kumar and Steenkamp (2007), retailers adopting a copycat strategy may primarily aim to (i) improve their negotiation power and margins and (ii) forego the product development risks and costs linked to an 'original product' strategy. Even though these effects may be hard to quantify, they seem to add to the conclusion that, even in the absence of immediate visual confusion, the PL copycat practice may be quite harmful to the leading national brands.

Third, in a somewhat similar vein, it can be expected that the imitation strategy becomes more detrimental to the original brand, as the visual similarity gets more striking than was the case in our empirical study. Even if increased package similarity does not bring about immediate visual confusion, it may cause the product experiences to become confused in memory and, unless the copycat's quality exceeds that of the original, produce detrimental reversed spillovers on the average quality belief of the imitated brand as well. This would further add to the negative consequences for the imitated brand. At the same time, too blatant imitations may make retailers 'walk a thin line', as reactance towards the copycat may be luring if its quality turns out to be too low (Van Horen et al. 2008; Warlop and Alba 2004).

Fourth, it would be relevant to drill down other types of copycatting-related spillovers, such as spillovers from advertising. These could appear directly, i.e. ads of the original NB benefiting the copycat PL, but also indirectly, i.e. ads driving choice of the original NB and resulting in consumption benefits for the copycat PL. Our model includes only the latter, and only implicitly so since we do not have advertising data, thereby leaving out another potential source of free-riding for the imitating brand. Interestingly, the degree of spillovers from ad messages might be driven by the specific advertising content: ad executions emphasizing the NB brand's genuine character and uniqueness possibly diminishing the copycat's potential to free-ride on its reputation. Intriguing, also, is the role of in-store display. In case of copycatting, it is not uncommon for the retailer to assign the imitating and imitated brand a prominent and adjacent position on the shelf – a practice also observed for our two data sets. Such joint and central placement may foster spillovers from the original to the copycat, but may also enhance attention to the imitated NB at the expense of NB competitors. Our model results implicitly reflect the impact of shelf placement, which we cannot separate out from brand utilities as it does not change over time in our data. Future research considering alternative displays may separate out this net placement effect. If it is positive, being copied by a superior quality PL could actually be beneficial to the leading national brand, and such superior-quality copycats could turn out to be 'friends'. Especially from a managerial perspective, these are important issues for future study, as they could help managers fine tune their look-alike strategies, or defensive reactions to them.

Fifth, an interesting issue is to what extent retailer characteristics affect the success of the imitation strategy. One possibility is that the effects are purely driven by actual quality differences between the original brand and the copycat in the specific product category. In that case, if their copycat is superior to the leading brand in one category but not in other, retailers should assess appropriateness of copycatting for each category separately. Conversely, the believability of the ‘same-quality’ signal through package similarity, and hence the spillover effects, may be strongly shaped by overall retailer equity, which could make the look-alike approach equally beneficial for high-equity retailers across the board. Insights into these phenomena would be relevant not just for retailers, but also for leading manufacturers in setting up their defenses vis-à-vis specific retailer accounts. Finally, our results were obtained for two traditional, Hi-Lo retailers adopting an umbrella-brand private label strategy. Whether our observed effects also pertain to hard discounters, or other retailers whose private label name is less clearly identifiable as a retailer brand, is a fascinating area for future study.

Sixth, like in previous chapters, our data do not cover major changes in retailer copycat policies. Our results are, therefore, based on two sources of inferences. First, we draw inferences from changes in consumer behavior as a result of changes in their experience with the brands. Second, we compare the dynamics in consumer behavior (i.e. consumer learning) for brand pairs involved in copycatting (i.e. a copycat PL and an original brand) vs. other brand pairs (i.e. a copycat PL and a non-imitated NB). Both sources of variation point in the direction consistent with our expectations. Even so, we should be cautious in deriving policy implications from our findings. Stronger claims could be made if we observed, for instance, the emergence of an imitation situation (i.e. a PL starting to imitate the trade-dress of an original brand) or the disappearance of copycatting (e.g. one of the involved brands revises its trade-dress), settings that we look forward to studying in the future.

Finally, as remarked earlier, our model extension is not structural in the sense that our cross-effects do not result from correlated belief priors (Erdem, 1998) or correlated consumption signals (Coscelli and Shum, 2004). Extending these structural models to incorporate the asymmetric spillover effects associated with copycatting is a worthwhile endeavor, and high on our research agenda.

5 General conclusions and directions for future research

Consumers seek to develop their beliefs, and minimize their uncertainty, about the quality of brands. While they can do so using multiple sources of information, brand beliefs are strongly shaped over time ("learned") through consumption experiences with these brands. Such learning is an important process from the point of view of consumers, firms, and the economy. Through consumption-based learning, consumers can identify brands that best fit their personal tastes. For firms, it offers the possibility to capitalize on their quality investments. From a societal perspective, learning may help ensure the benefits of competition, as brands need to measure up to their rivals in terms of quality.

Consumption-based learning is not only an important process, but also an intricate and multi-faceted one. While consumer learning is strongest for new and complex products, it is also present in mature contexts albeit with vast differences in the rate of learning across product categories and across individuals. As to the nature of the effect, there are two sides to learning: consumption experiences shape the average level of brand quality beliefs, but also a consumer's uncertainty or the 'precision' of these beliefs. Furthermore, consumption not only reveals information about the brand itself, but may also spill over to other, similar brands – a process that we refer to as cross-brand learning. Such cross-brand learning may affect brand performance in several ways. On the one hand, the reputation earned by a brand can spill over to its rivals and effectively subsidize them, increasing their share at the expense of the originally consumed brand. On the other hand, these spillovers can be reciprocal, and possibly even beneficial for all brands involved. Perceived brand-quality in terms of quality level and quality uncertainty are key determinants of private label usage, and different forms of cross-brand learning have a significant influence on the perceived quality of private labels.

The essays in this thesis zoom in on these aspects of consumption-based learning. Below, we start by summarizing the setup and findings of the separate chapters. Next, we place these results in a broader perspective – highlighting take-away insights across the different essays. We end with a discussion of limitations and future research areas to be addressed.

5.1 Summary of Findings

Prior research mainly associates learning with infrequently-purchased, high involvement or strongly evolving categories, such as pharmaceuticals. However, recent empirical findings suggest that consumption-based quality learning *does* take place in more established categories. In chapter two of this thesis we expand the literature, which examines only a few mature-category products and does not systematically look into the drivers of learning for mature packaged goods categories. In particular, we are interested in (1) the prevalence and magnitude of learning about frequently-purchased consumer goods, (2) the variation in learning across packaged goods categories and across households, and (3) the underlying learning drivers. Our household-level brand choice models apply Bayesian learning in 20 product categories, yielding category- and household-specific posterior estimates of the parameters showing the extent to which consumer knowledge is updated with new consumption-based information. We find that learning is present in almost all categories, albeit very weak in some of those categories, and that cross-category and cross-household variation are both vast and of a comparable magnitude. Notably, we observe very low correlations in cross-category household learning, suggesting that consumption-based knowledge updating is not a household trait. Our study reveals that learning is negatively associated with variety seeking, positively linked to perceived category risk and category expensiveness, and more prevalent among consumers with high category purchase frequency.

Building on this evidence of own-brand learning for packaged consumer goods, chapter three of this thesis zooms in on two novel features in the learning literature, by studying *cross-brand* learning effects, and focusing on retailer-owned or *private label* brands. In doing so, this chapter attempts to bridge two views of private labels: one, that private labels are a key tool for store differentiation, and two, that consumers do not distinguish between PLs of different chains. To investigate this issue, we raise the questions of *when* investments in PL quality set retailers apart from competitors, and *when* they subsidize rival PLs. We expect that consumers generalize knowledge from product experience across PLs, and that such cross-brand learning depends on perceived quality similarity, which decreases with actual brand differences and as consumers learn. Building on earlier work in Bayesian learning models, we propose a brand choice model that captures conditional cross-brand learning through quality belief spillovers (consumers adjust beliefs about PL quality on the basis of consumption experience) and familiarity spillovers (uncertainty about a PL diminishes with rival PL consumption).

We calibrate this model on a household scanner panel dataset in the liquid dish detergents category, focusing on households that shop at multiple stores. The results yield evidence of cross-retailer PL learning, and reveal that familiarity spillovers dominate quality belief spillovers. From a private label brand management perspective, these results seem to favor herd (average quality) and free-riding (below average quality) positioning strategies, especially for retailers whose clientele primarily consists of multiple-store shoppers. Retailers pursuing quality leadership can break away from the mainstream PL image by establishing a sufficiently large quality gap, but, by doing so, forego the benefits of familiarity spillovers.

The fourth chapter of the thesis further pursues the implications of cross-brand learning, but from an entirely different perspective. Specifically, this chapter seeks to assess whether copycat private labels are a ‘friend’ or a ‘foe’ of the leading national brands that they imitate. On the one hand, copycatting can lead to quality spillovers from the imitated national brand to the copycat private label, or even to two-way spillovers between the brands. This would make the copycat a ‘foe,’ free-riding on the reputation of the original national brand. On the other hand, if consumers experience disappointing quality with the imitator brand, this may incite ‘reactance’ against the copycat and ‘rewarding’ behavior towards the original brand, thus turning the copycat into a ‘friend’. To investigate these phenomena, we extend existing models by accommodating dynamic cross-brand learning among the original national brand and the private label copycat. We calibrate it on household panel scanner datasets from two product categories in two retail chains. Our results indicate that, even if the trade-dress imitation is not exact and not blatant enough to cause visual confusion, there are non-negligible spillover effects from the original brand to the imitator brand. We find that consumers do shape their quality beliefs of copycat private labels based on consumption experiences with the original national brand. These spillovers trigger choice shifts, especially from the imitated to the imitator brand, which only gradually dilute brand’s choice share when true quality differences can be perceived, or as consumers become knowledgeable about brands. While we do find partial evidence of ‘rewarding’ behavior, this positive effect for the national brand is overwhelmed by the negative quality spillover implications. We find no evidence of memory confusion or assimilation (i.e., quality beliefs about the original being affected by copycat usage), or of experience-based ‘reactance’ (i.e. consumers refuting the imitating private label if its quality appears too low compared with the imitated national brand). In all, our findings document that private labels with a quality level exceeding that of the leading national brand do not become more threatening if they adopt a copycat approach. For lower quality copycats, even though they may exhibit some ‘friendly’ features in the form of rewarding effects for the original, the overall impact of their imitation strategy is detrimental to the national brand. Even non-blatant imitations, for which the traditional litigation argument of ‘visual’ confusion is hard to uphold, may cause a sizeable reduction in the original’s choice share, and warrant manufacturer attention.

5.2 Implications

The findings presented in this thesis generate a number of substantive and managerial insights. As we already discussed specific implications in the previous chapters, we do not repeat them here. Instead, we discuss some of the broader implications of our findings below.

Consumer brand quality learning is important but easily overlooked

Recent study documents that early entry may endow leading national brands with a sustained advantage in terms of share and quality beliefs, even years after the introduction (Bronnenberg et al. 2009). At the same time, the presence of consumer learning through consumption in mature categories suggests that these established brands do need to actively 'safeguard' their quality beliefs vis-à-vis new manufacturer brand entrants or, in many instances, private labels. Otherwise, these new challengers will gradually gain ground as consumers become less uncertain about them. We find that the changes in brand market share resulting from quality learning may be substantial and therefore managerially relevant. However, these changes come about gradually, and take place at different rates for different consumers. This makes it rather difficult for managers to appreciate or even detect quality learning induced changes in brand market share, particularly when their focus is on short term brand returns. Established brands commanding large market shares may, as a result, be tempted to "rest on their laurels." To avoid this, managers should monitor their brands using models capturing long term evolution of the market place, such as the structural learning models used here (for broader discussion on structural models see Bronnenberg et al. 2008; Chintagunta et al. 2006) or reduced form models with time varying parameters (e.g. Ataman et al. 2010).

Brand quality improvements impact brand performance in multiple ways

Continuous investments in quality improvement may help incumbents to 'stand their ground.' Our results corroborate previous insights that quality improvements, once communicated to consumers, may enhance a brand's market share directly. Moreover, quality improvements can bolster brand performance indirectly by leveraging the effectiveness of other marketing efforts – particularly those fostering product trial, e.g. price promotions and advertising. These efforts can help the brand communicate its new, improved quality and thereby increase the propensity of repeat purchases following trial. A decline in product quality acts in a similar way but has the opposite effect: it leads to a drop in sales and effectiveness of marketing efforts. For instance, van Heerde et al. (2007) show a drop in baseline sales and in the elasticities of marketing efforts following a product harm crisis. In addition to these effects, we empirically demonstrate that quality investments can set the brand apart from competition and thereby prevent its reputation from spilling over to other, similar brands. Our results suggest, however, that to prevent such spillovers, the quality investments need to be substantial to clearly distinguish and “shield” the investing brand.

Cross-brand learning hampers differentiation, but this can be beneficial

Cross-brand learning can have a substantial impact on a brand’s market share. In the copycat private label context, which we study in chapter four, the effect is negative for the national brand. This finding is related to other research showing that brands are harmed by being too similar to their competitors (Pullig et al. 2006; Warlop et al. 2005). Interestingly, we also find that cross-learning is not always “bad” for the source brand. In cross-brand learning among private labels, which we document in chapter three, the effect is positive for all involved brands. In all, our findings suggest that, for cross-brand learning to have a positive impact on the involved players, it needs to be reciprocal (which means that all brands receive spillovers from one another) and the brands’ quality positioning must be similar. Conversely, cross-brand learning can have a negative impact on a brand (i) when that brand is a source but not a receiver of familiarity spillovers, or (ii) when it receives spillovers from a lower quality brand, and the quality belief spillovers outweigh the uncertainty reduction effects. These findings present managers with interesting trade-offs. Brands wishing to differentiate themselves from competitors need to choose a radically different quality positioning and/or packaging. In doing so, they occupy a unique place in the mind of the consumer, and escape from the negative consequences of cross-brand effects. However, managers need to weigh this against the potential benefits of cross-brand spillovers (i.e. risk reduction), which they forego by setting their brand apart.

Private labels' success is partly due to efficiencies in reputation building

Prior research (Dekimpe and Hanssens 1995; Hoch et al. 2006) and industry reports (AC Nielsen 2005) indicate that while the market share of most national brands in the long run remains stationary, private label brands gain market share over time. Our findings suggest that the category sales share captured by private labels, especially those that imitate leading national brands' packages, is influenced by their efficiency in reputation building. Whereas each national brand builds its reputation on its own, private labels, to some extent, develop their reputations collectively. Moreover, copycat private labels free-ride on the reputation of the imitated national brands. Had these processes not taken place then, ceteris paribus (that is, brand qualities and marketing efforts remaining as they are), private labels' market share would be lower.

5.3 Future research

In addition to generating a number of insights, the essays in this thesis also raise additional questions, and set the stage for several new research avenues. To complement the specific research suggestions already discussed in the respective chapters, we cover some general future research directions below.

Distinguishing between learning and other dynamics

A limitation of choice models with Bayesian learning is that they typically do not accommodate other forms of dynamics that may give rise to somewhat similar data patterns. Such overlooked dynamics include drivers of positive state dependence, like inertia (consumers sticking with the previously bought brands out of "habit" or laziness) or endowment effects (consumers becoming emotionally attached to a brand as a result of consuming it), drivers of negative state dependence, like variety seeking (consumers deriving utility from change) (Erdem 1996; Inman et al. 2008), or other factors that trigger brand switching, such as taste evolution (Biehl 2001; Dhar and Simonson 2003) or brand quality evolution (Lovett 2008). The outcomes of these dynamic processes may be quite important

(Bronnenberg et al. 2009) and quite different from those of learning. For instance, brand purchase and consumption will always have a positive impact on the brand's future purchase propensity in cases of inertia, while it may – if the experienced consumption quality is disappointing (i.e., substantially below the prior quality belief) – reduce the likelihood of repurchase in cases of learning. Even so, in a number of instances, these other forms of dynamics may be hard to separate from "true" quality learning effects. Future research should determine how these additional forms of dynamics can be controlled for, by extending the model and possibly using richer data than the commonly adopted household scanner datasets. Assessing the magnitude of these effects relative to learning may shed additional light on the consequences of not controlling for them, and on whether the policy implications derived from learning models should be modified.

Retail branding

Cross-learning models, similar to the ones presented in this thesis, can be applied to study retail branding strategies. An important question in this sparsely researched field is whether "a strategy of multiple private label brand names is more effective […] than having a single private label under the store name" (Ailawadi and Keller 2004 p. 339). To answer this question we must also ask (i) what is the effect of a private label sharing the brand name with the chain (spillovers between service and product brands)?, and (ii) what is the effect of using a single brand name encompassing all product categories in which a retailer has its own products, vs. multiple brand names encompassing narrower sets of categories (cross-category spillovers)?

Spillovers between product and service brands

Using the chain name for the private label products can have an effect on private label choice share. The retailer name is expected to reduce consumer uncertainty about the private label, and our results suggest that familiarity spillovers may constitute an important utility enhancer. However, the chain name may also have strong associations that would not benefit product sales (Bhat and Reddy 2001). The net effect of using the retail chain name to brand the private label products, on the choice shares of these private label products (or, for that matter, of the chain itself), is therefore an interesting area for further study.

Cross-category spillovers

The effect of using one brand name for private label products in all categories rather than multiple names in subsets of categories is also uncertain. Both approaches can lead to umbrella effects among categories using the same brand name (Erdem 1998; Erdem and Sun 2002; Sayman and Raju 2004). The potential advantage of the "one brand approach" is that the spillovers would span a broader range of categories. On the other hand, what can benefit the "multiple, narrow brands approach" is that each brand can include related categories and consequently enjoy stronger spillovers (Aaker and Keller 1990; Broniarczyk and Alba 1994; Park et al. 1991). The empirical question is, then, in which of these two cases are umbrella effects more beneficial to the retailer?

Tackling these questions about the effect of retail branding strategies – same or different name for chain and private label products?, single or multiple private label brand names across categories? – is a challenging task. A cross-sectional approach in which one might compare the performance of branding strategies across retail chains would likely be hindered by the researcher's limited ability to control for numerous chain-specific confounding variables. A time-series approach is hampered by the fact that brand strategy changes are very rare, i.e., few chains switch between a "one broad brand" strategy and a "multiple, narrower brands" strategy. Yet, a promising research opportunity is to focus on a rare 'natural experiment' where a retail chain actually changes its branding strategy, and follow up on the consequences of such events for household-level dynamics, such as cross-category learning, and learning among chain brands and private label brands. The retailer Clout recently moved from using multiple brand names to labeling its products with the common name "Everyday Selection," presenting an interesting research possibility.

In a related vein, future research should aim to compare the relative influence on a private label exerted by spillovers from rival private label brands (Chapter 2) or imitated national brands (Chapter 3) in the same product category, the store's own private label brand in other categories, and same-store or competing-store private labels from different tiers (e.g. budget or premium, as opposed to standard, private labels).

Within category brand scope

This last research idea considers strategic implications of the cross-category and cross-domain (retailing service vs. products) scope of the retailer's brand. Future research could tackle other issues related to brand scope, for instance within a product category. Firms offering many SKUs in a category face a choice between branding all SKUs with a common name or using multiple brand names within that category. As in the case of cross-category brand scope, the "one brand strategy" is expected to stimulate cross-SKU learning and consequently economize on costs of reputation building and on other marketing efforts (Balachander and Ghose 2003). The novel aspect of brand scope considered in the context of one category is that a "one brand strategy" may be unattractive to consumers who are variety seeking with regard to brand name (Inman et al. 2008). Prior research documents both effects, but little is known about their relative magnitude and, consequently, the net advantage of using one versus multiple brand names. Extending SKU choice models (Fader and Hardie 1996) with cross-learning might shed more light on this issue.

When to comply and when to deviate from the category trade dress code?

Chapter four of this thesis underscores the importance of package similarity in driving consumer brand evaluations. Future research should explore this issue further. Brands from the same category commonly share a set of package design features, a phenomenon referred to as the "trade dress code". This alignment in the package design choices of brands is an interesting, yet little studied phenomenon (Warlop and Alba 2004; Warlop et al. 2005). Deviation from the category code can allow the brand to gain more differentiation from competition and, therefore, be more easily located on the shelf (van der Lans et al. 2008) or develop stronger quality associations (Warlop et al. 2005). However, chapter three in this thesis suggests that compliance with the trade dress could allow the brand to benefit from the familiarity that consumers have developed with the category. Future research could build a conceptual framework predicting which type of brands, and under what conditions, stands to benefit more from compliance versus deviation from the category code. Such a framework could be tested using Bayesian learning models pertaining to brands with a more or less 'deviant' trade dress, and linking the impact of the brand's deviation from the category code to other characteristics of the brand and competitive context.

Appendix 1

TABLE A1.1 NOTATION OVERVIEW

Symbol	Description
Indices and (vectors of) indicators	
c	Index for product category
C	Number of sample categories
d_{jct}	Indicator equal to 1 if brand j in category c was consumed at purchase occasion t and 0 otherwise*
$D_{ct,i}$	Vector of purchase indicators djct of household i up to purchase occasion t
$E_{ct,i}$	Vector of consumption signal Gjct received by household i up to purchase occasion t
J_c, N_c	Number of sample brands, and number of households, respectively, in category c
j, k	Indices for brand
M	Index for unit of a product
M_{ct}	Number of product units purchased by the consumer in category c on the purchase occasion t*
t, h	Indices for purchase occasion
T_{ci}	Number of purchases in category c made by household i during the sample period
w_{ct}	Week index for purchase occasion t in category c
$z_{jct,i}$	Indicator equal to 1 if brand j in category c was available to household i at purchase occasion t and 0 otherwise.
Utility and its determinants	
r	Risk aversion parameter*
U_{jct}	Utility of brand j in category c at purchase occasion t*
X_{jct}	Utility determinants for brand j in category c at purchase occasion t other than quality belief*
β	Consumer's sensitivity parameters to utility determinants in Xjt*
ε_{jct}	i.i.d. extreme value component of utility observed by the consumer, unobserved by the researcher*
Quality and quality belief	
q_{jc}	True quality of brand j in category c*
Q_{jct}	Quality belief of brand j in category c on purchase occasion t*
μ_{jct}	Mean quality belief of brand j in category c on purchase occasion t*
σ^2_{jct}	Uncertainty or variance in quality belief for brand j in category c at purchase occasion t*
Learning and forgetting	
b_c	Parameter capturing the rate of forgetting*
I_{tc}	Consumer's information set in category c at purchase occasion t*
g_{jctm}	Consumption signal of one unit of brand j in category c on purchase occasion t*
G_{jct}	Average over a series of mct consumption signals gjct for brand j in category c on purchase occasion t
σ_{gc}	Standard deviation of the consumption signal in category c*
Household heterogeneity	

v_{b_c}, ς_{b_c}	Mean and variance across households of the parameter b capturing the extent of forgetting, i.e., $b_c \sim \log - N(v_{b_c}, \varsigma_{b_c})$
$v_{q_{jc}}, \varsigma_{q_{jc}}$	Mean and variance across households of the true quality parameter, i.e., $q_{jc} \sim \log - N(v_{q_{jc}}, \varsigma_{q_{jc}})$
v_{r_c}, ς_{r_c}	Mean and variance across households of the risk aversion parameter, i.e., $r_c \sim \log - N(v_{rc}, \varsigma_{rc})$
$v_{\beta_c}, \varsigma_{\beta_c}$	Vectors of mean and variance across households of the parameters β, i.e., $\beta_c \sim N(v_{\beta_c}, \varsigma_{\beta_c})$
$v_{\sigma_{gc}}, \varsigma_{\sigma_{gc}}$	Mean and variance across households of the standard error of the consumption signal, i.e., $\sigma_{gc} \sim \log - N(v_{\sigma_{gc}}, \varsigma_{\sigma_{gc}})$
Other notation	
Ωc,i	Set of parameters, i.e., Ωci = aa

* The subscript i for consumers is dropped

Estimation issues in the first stage of the analysis

Identification. To obtain identification, in each of the category-specific models we fix one of the true quality population mean parameters across households (i.e., $v_{q_{jc}} = 0$), the uncertainty regarding brand quality at purchase occasion t = 0 for all brands (i.e., $\sigma_{c0}^2 = 1$). The remaining parameters are to be estimated. All parameters are summarized in the vector $\alpha_c \equiv \{v_{q_{jc}}, \varsigma_{q_{jc}}, v_{\beta_c}, \varsigma_{\beta_c}, v_{\sigma_{gc}}, \varsigma_{\sigma_{gc}}, v_{b_c}, \varsigma_{b_c}, v_{r_c}, \varsigma_{rc}, \sigma_{c0}^2\}$.

Dealing with left truncation. We do not observe consumers from the beginning of their consumption history and therefore face the problem of left truncation. Similar to previous authors (e.g., Mehta, Rajiv, and Srinivasan 2004), we include an initialization period. We first estimate the model with a subsample of 40 weeks and use the resulting $\mu_{jct,i}$ and $\sigma^2_{jct,i}$ to initialize the estimation of the remaining data. We set the initial quality beliefs at the beginning of the initialization period equal to the mean of the true quality across the population and, for identification (see above), fix the initial variance of the quality beliefs to 1, such that $\mu_{jct=0,i} = v_{q_{jc}}$ and $\sigma_{c0}^2 = 1$.

Likelihood function. For any consumer i, the likelihood of the entire purchase history in category c $D_{T_i c,i}$, conditional on $\{\Omega_{c,i}, \mathrm{E}_{T_i c,i}\}$, is:

$$L_i\left(D_{T_i,i} \mid \Omega_i, \mathrm{E}_{T_i,i}\right) = \prod_{t=1}^{T_i}\prod_{j=1}^{J} \Pr\left(d_{jt,i} = 1 \mid \Omega_i, \mathrm{E}_{t,i}\right)^{d_{jt,i}}.$$

We denote the p.d.f. of parameters in Ω_i as $u_\Omega(\Omega_i)$ and the p.d.f. of $\mathrm{E}_{T_i,i}$ as $u_E(\mathrm{E}_{T_i,i})$. The unconditional likelihood of household i purchase history $D_{T_i,i}$ is:

$$L_i\left(D_{T_i,i} \mid \alpha_c\right) = \int_{\Omega_i}\left(\int_{\mathrm{E}_{t,i}} L_i\left(D_{T_i,i} \mid \Omega_i, \mathrm{E}_{T_i,i}\right) u_E\left(\mathrm{E}_{T_i,i}\right) d\mathrm{E}_{T_i,i}\right) u_\Omega\left(\Omega_i\right) d\Omega_i .$$

Because this likelihood involves multidimensional integrals, numerical computation is prohibitively expensive. Therefore, in line with previous studies, we resort to simulated likelihood. Using F sets of scrambled Halton draws (Train 2003) for the coefficients in Ω_i and the consumption signals in $\mathrm{E}_{T_i,i}$, we obtain an estimate of L_i:

$$\hat{L}_i\left(D_{T_i,i} \mid \alpha_c\right) = \sum_{f}^{F}\left(L_i\left(D_{T_i,i} \mid \Omega^f, \mathrm{E}^f\right)\right).$$

We set F = 100, because larger values are not feasible given the computational demands of the model. As a robustness check, we run the model with different sets of draws, and the results do not change.

The log-likelihood for N households is:

$$LL\left(\left\{D_{T_i,i}\right\}_{i=1}^{N} \mid \alpha_c\right) = \sum_{i=1}^{N} \ln \hat{L}_i\left(D_{T_i,i} \mid \alpha_c\right).$$

We estimate the parameters in α_c by maximizing this likelihood:

$$\alpha_{c,MLE} = \arg\max_{\alpha} LL\left(\left\{D_{T_i,i}\right\}_{i=1}^{N} \mid \alpha_c\right).$$

TABLE A1.2 FIT OF FIRST STAGE MODEL, COMPARED WITH STATIC MODEL AND MODEL WITH 'LAST BRAND PURCHASED' VARIABLE

	Model without dynamics			Bayesian learning model		
Category	**Log-likelihood**	**BIC**	**AIC**	**Log-likelihood**	**BIC**	**AIC**
Spices and herbs	-960.340	2016.659	1950.68	-942.1264	2005.826	1922.253
Rice and pasta	-1435.812	2955.357	2897.625	-1381.741	2885.86	2801.482
Liquid dish detergent	-139.9369	351.6008	305.8739	-109.7788	324.3893	257.5577
Dressing	-2225.441	4552.016	4476.883	-2240.152	4628.113	4518.304
Milk substitutes	-336.3434	758.325	698.6868	-310.2859	745.7352	658.5717
Mouth hygiene	-175.0828	418.1004	376.1657	-133.5901	366.4693	305.1802
Fish and seafood	-878.024	1842.719	1782.048	-852.2836	1831.239	1742.567
Warm drinks	-2219.722	4539.873	4465.444	-2144.018	4334.388	4300.036
Fabric softeners	-136.615	339.6072	299.23	-135.4948	368.0026	308.9896
Biscuits and cookies	-3479.924	7063.708	6985.848	-3489.34	7130.475	7016.68
Bread substitutes	-740.7767	1574.785	1507.553	-694.2892	1524.84	1426.578
Toilet and kitchen tissues	-1554.661	3199.57	3135.322	-1534.295	3200.492	3106.591
Liquid laundry detergent	-93.6964	219.6965	213.3927	-75.3671	163.1587	160.7342
Female hygiene and diapers	-391.5288	851.2003	809.0576	-380.7654	861.124	799.5308
Cleaning materials	-184.8815	431.2191	395.763	-154.1149	398.0501	346.2298
Cleaners	-328.7823	725.912	683.5645	-305.3454	710.5832	648.6908
Vinegar	-229.7861	531.6085	485.5721	-224.0826	553.4492	486.1652
Solid dish detergent	-102.4225	262.4456	230.845	-73.8755	231.9366	185.7511
Ice-cream	-746.3251	1573.698	1518.65	-715.3606	1549.175	1468.721
Deodorant	-284.1224	635.5347	594.2448	-243.8725	586.0919	525.7451

TABLE A1.3 PARAMETER ESTIMATES (MEANS AND STANDARD DEVIATIONS OF THE POPULATION MIXING DISTRIBUTIONS) OF FIRST STAGE MODELS

		Spices and herbs		Rice and pasta		Liquid dish detergent		Dressing		Milk substitutes		Mouth hygiene		Fish and seafood		Warm drinks		Fabric softeners		Biscuits and cookies	
		Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE
True quality, Brand 1	Mean	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed
	St.Dev.	0.366	0.974	0.379	0.172	0.859	0.516	0.338	1.355	0.6	0.272	-0	0.017	0.502	0.213	0.532	0.114	0.936	0.631	1.013	0.103
True quality, Brand 2	Mean	1.147	0.807	0.931	0.361	0.58	0.757	0.852	2.541	0.81	0.51	1.159	0.552	0.255	0.397	0.592	0.331	0.32	0.788	-0.68	0.296
	St.Dev.	0.813	0.537	-0	4E-07	-0.22	0.778	0.46	3.938	0.486	0.292	0.217	0.419	0.513	0.209	0.426	0.105	0.38	0.595	0.734	0.099
True quality, Brand 3	Mean	-2.28	0.608	1.003	0.36	-0.09	0.59	0.794	2.956	1.086	0.446	0.686	0.646	0.159	0.418	0.946	0.33	0.107	0.777	-0.51	0.316
	St.Dev.	-1.25	0.187	0.375	0.155	-0.57	1.081	4E-07	2E-06	-0.26	0.244	0.556	0.417	0.275	0.234	0.475	0.112	0.354	0.933	0.664	0.106
Uncertainty at t=0	Mean	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed
Cons. signal var.	Mean	0.566	0.823	1.256	0.376	-3.17	0.948	1.214	4.942	1.2	0.493	-0.1	0.734	0.657	0.431	1.224	0.324	-0.39	0.746	0.134	0.299
	St.Dev.	0.456	0.679	0.896	0.133	0.944	1.001	0.543	2.048	0.409	0.274	0.683	0.431	0.512	0.183	0.448	0.106	0.561	0.967	0.592	0.108
Risk aversion	Mean	1.264	0.578	0.971	0.33	1.551	0.71	0.999	2.764	1.162	0.397	1.102	0.454	0.567	0.382	0.972	0.287	0.457	0.689	0.046	0.298
	St.Dev.	-1.24	0.365	0.221	0.143	-1.07	0.469	0.188	0.628	0.383	0.146	0.286	0.339	0.272	0.221	0.139	0.129	1.185	0.579	0.271	0.118
Forgetting	Mean	-2.31	0.991	-26.9	79.46	-1.27	1.002	-27.3	-122	-26.9	73.34	-6.64	1.201	-25.4	36.25	-16.4	5.778	-22	85.91	-7.8	0.671
	St.Dev.	0.678	0.846	0.5	3.756	-0.13	1.011	0.5	2.652	0.5	3.29	0.598	0.735	-1.18	4.327	-0.03	0.264	0.5	2.228	-0.7	0.477
Feature display	Mean	-28.3	84.7	0.696	0.459	4.52	1.427	1.585	6.831	3.277	0.878	1.488	49.97	2.458	0.703	1.093	0.392	3.268	0.707	0.781	0.366
	St.Dev.	0.355	28.03	1.472	0.211	-0	0.001	0.757	2.589	1E-05	4E-05	1.084	0.472	-0	7E-06	1.27	0.137	-0.02	0.118	1.307	0.122
Feature only	Mean	1.327	4.524	0.459	0.503	0.601	1.474	0.039	0.196	-2.05	1.451	1.871	0.915	1.479	0.594	0.397	0.389	2.358	1.426	0.406	0.378
	St.Dev.	0.419	12.11	1E-05	6E-05	0.012	0.051	0.808	3.168	7E-05	4E-04	-0	0.007	1.012	0.648	-0.78	0.154	3.32	0.792	-0.98	0.14
Display only	Mean	0.333	3.763	2.038	0.665	4.805	1.719	-0.19	-0.42	1.786	1.158	1.715	49.97	1.424	0.849	-0.1	0.457	0.753	0.926	0.511	0.383
	St.Dev.	0.5	13.76	1.462	0.177	0.012	0.049	0.766	2.797	-0	0.002	0.036	0.282	-0	3E-05	-0	0.004	1.395	1.755	9E-06	4E-05
Price	Mean	-3.87	0.656	-0.96	0.373	0.517	0.774	0.023	0.1	0.186	0.656	0.005	0.021	-0.01	0.355	0.042	0.286	-1.14	0.804	-0.29	0.29
	St.Dev.	1.417	0.317	1.355	0.125	2.27	0.483	1.058	5.877	1.42	0.253	0.367	0.307	0.486	0.131	0.489	0.085	1.358	0.577	0.836	0.09

TABLE A1.3 CONTINUED

		Bread substitutes		Toilet and kitchen tissues		Liquid laundry detergent		Female hygiene and diapers		Cleaning materials		Cleaners		Vinegar		Solid dish detergent		Ice-cream		Deodorant	
		Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE	Par. Est.	SE
True quality, Brand 1	Mean	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed
	St.Dev.	7E-06	4E-05	0.728	0.088	0.625	Fixed	0.537	Fixed	0.694	0.377	0.002	0.008	1.089	0.315	-0.77	0.446	0.252	0.276	0.196	3.954
True quality, Brand 2	Mean	0.908	0.412	0.621	0.326	0.757	0.561	0.746	Fixed	0.914	0.521	0.93	0.457	-0.51	0.588	1.317	0.603	0.87	0.416	1.316	1.289
	St.Dev.	0.168	0.222	0.608	0.17	0.294	Fixed	-0.73	Fixed	-0	3E-04	-0.03	0.633	-0	0.001	-0.12	0.858	0.471	0.21	0.405	0.697
True quality, Brand 3	Mean	0.907	0.386	0.71	0.294	0.274	0.503	0.847	Fixed	1.256	0.591	1.005	0.456	-0.55	0.561	1.148	0.678	0.778	0.435	-2.44	0
	St.Dev.	-0.33	0.237	0.711	0.086	0.729	Fixed	0.538	Fixed	0.589	0.438	-0.15	0.281	0.114	0.5	-0.4	0.474	-0.38	0.228	-1.51	3.325
Uncertainty at t=0	Mean	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed	0	Fixed
Cons. signal var.	Mean	0.855	0.474	1.163	0.329	-0.19	0.561	1.034	Fixed	0.214	0.647	0.659	0.513	-15.5	1.277	-15.8	38.47	0.636	0.498	0.475	2.179
	St.Dev.	0.891	0.258	0.916	0.114	0.305	Fixed	0.806	Fixed	0.813	0.4	-0.67	0.332	0.5	1.309	0.996	8.149	0.751	0.241	0.878	1.531
Risk aversion	Mean	1.048	0.347	1.392	0.224	1.019	0.441	1.577	Fixed	1.139	0.441	0.987	0.414	0.123	0.466	1.362	0.532	0.852	0.408	0.633	0.973
	St.Dev.	-0.15	0.205	-0.26	0.071	7E-04	Fixed	-0.37	Fixed	-0.24	0.356	0.3	0.316	0.334	0.348	0.54	0.218	0.382	0.202	1.395	0.801
Forgetting	Mean	-25.4	40.29	-2	0.902	-4.2	0.804	-2.51	Fixed	-6.29	1.157	-24.3	77.83	-4.25	1.215	-9.67	260.1	-23.8	-104	-3.04	78.48
	St.Dev.	0.5	4.341	0.499	0.791	0.796	Fixed	0.815	Fixed	1.352	0.412	0.5	2.527	0.5	0.911	5E-04	0.002	0.5	3.956	1.045	7.113
Feature display	Mean	1.795	0.896	0.999	59.83	4.17	Fixed	1.007	Fixed	8.755	1.508	2.276	0.531	-55.9	2.844	2.665	1.305	2.282	0.531	1	Fixed
	St.Dev.	-0	3E-04	1.583	10.7	-0.01	Fixed	0.502	Fixed	8E-05	3E-04	0.644	0.661	11.06	2.549	2.239	1.34	1E-04	5E-04	0.355	Fixed
Feature only	Mean	-0.29	0.692	1	3.075	7.772	Fixed	0.985	Fixed	8.749	1.525	-0.12	0.703	-46.5	2.87	3.126	2.03	0.812	0.63	4.288	188.6
	St.Dev.	4E-06	3E-05	0.156	1.42	0.033	Fixed	4.124	Fixed	2.579	1.486	0.151	2.199	-1.92	4.336	-0.03	0.146	5E-04	0.002	1.005	5.891
Display only	Mean	-0.44	0.632	1	2.115	3.668	Fixed	1.003	Fixed	-0.37	1.408	1.541	0.939	1.01	0.984	1.782	1.427	0.663	0.847	0.983	2.203
	St.Dev.	5E-05	4E-04	-0.24	7.073	-0.02	Fixed	1.787	Fixed	4.839	2.4	0.002	0.01	1.267	0.537	-0	0.007	0.001	0.005	0.48	4.656
Price	Mean	-0.11	0.413	-0.94	0.194	-0.1	Fixed	-1.46	Fixed	1.165	0.693	-0.14	0.589	-0.38	0.62	-0.22	0.705	-0.25	0.496	-3.36	0.693
	St.Dev.	0.791	0.195	1.462	0.045	0.631	Fixed	0.465	Fixed	0.968	0.497	1.101	0.278	0.008	0.048	6E-04	0.003	0.886	0.207	3.264	0.258

TABLE A1.4 CROSS-CATEGORY CORRELATIONS OF LEARNING PARAMETERS

	Spices and herbs	Rice and pasta	Liquid dish detergent	Dressing	Milk substitutes	Mouth hygiene	Fish and seafood	Warm drinks	Fabric softeners	Biscuits and cookies	Bread substitutes	Toilet and kitchen tissues	Liquid laundry detergent	Female hygiene and diapers	Cleaning materials	Cleaners	Vinegar	Solid dish detergent	Ice-cream
Spices and herbs	1.000																		
Rice and pasta	-0.096	1.000																	
Liquid dish detergent	-0.117	0.046	1.000																
Dressing	0.116	-0.044	0.075	1.000															
Milk substitutes	0.060	0.116	0.016	-0.026	1.000														
Mouth hygiene	0.166	0.036	0.343	0.062	0.020	1.000													
Fish and seafood	-0.216	-0.005	-0.005	-0.062	-0.019	-0.005	1.000												
Warm drinks	-0.011	-0.129	-0.117	0.098	-0.079	0.010	-0.057	1.000											
Fabric softeners	-0.069	-0.106	0.044	-0.086	-0.163	-0.501	-0.100	-0.055	1.000										
Biscuits and cookies	-0.026	-0.078	-0.091	0.155	-0.168	0.096	-0.046	0.056	-0.088	1.000									
Bread substitutes	0.084	0.037	-0.240	-0.025	0.133	0.004	-0.031	-0.068	-0.131	0.067	1.000								
Toilet and kitchen tissues	0.100	0.020	-0.006	-0.012	-0.105	0.086	0.061	-0.045	0.246	-0.061	0.267	1.000							
Liquid laundry detergent	0.132	-0.012	-0.157	0.220	0.102	0.271	0.345	0.189	-0.057	0.275	-0.009	-0.029	1.000						
Female hygiene and diapers	0.199	-0.105	-0.128	0.273	0.024	0.216	-0.124	0.004	-0.114	0.099	-0.013	-0.011	0.217	1.000					
Cleaning materials	0.056	-0.165	0.088	0.040	-0.013	0.060	-0.220	0.185	-0.054	0.068	-0.136	0.096	0.154	0.039	1.000				
Cleaners	-0.014	-0.096	0.003	-0.056	0.121	0.196	-0.095	-0.133	-0.224	-0.187	-0.019	-0.010	-0.433	0.191	0.060	1.000			
Vinegar	-0.008	0.135	-0.123	0.022	-0.231	-0.034	-0.009	0.012	-0.055	0.181	-0.004	-0.038	0.411	-0.013	-0.054	-0.215	1.000		
Solid dish detergent	0.096	-0.134	0.176	0.064	-0.066	0.300	0.044	0.112	-0.193	-0.075	-0.224	-0.025	0.217	0.120	0.119	0.031	-0.196	1.000	
Ice-cream	0.006	-0.061	0.113	-0.066	0.182	-0.114	-0.128	-0.299	0.217	-0.005	-0.028	-0.095	0.124	0.024	0.054	0.127	-0.040	-0.002	1.000
Deodorant	-0.042	-0.102	0.080	-0.067	-0.018	0.054	-0.067	-0.154	-0.508	0.051	-0.110	-0.077	0.120	-0.040	-0.170	0.210	0.041	-0.066	0.813

Appendix 2

TABLE A2.1 NOTATION OVERVIEW

Symbol	Description
Indices and (Vectors of) Indicators	
c	Index for retail chain.
d_{jt}	Indicator equal to 1 if brand j was consumed at purchase occasion t and 0 otherwise*.
$D_{t,i}$	Vector of purchase indicators d_{jt} of household i up to purchase occasion t.
$E_{t,i}$	Vector of consumption signal $G_{jt,i}$ received by household i up to purchase occasion t.
J, C, N	Number of sample brands, retail chains, and households respectively.
j, k	Indices for brand.
m	Index for unit of a product.
M_t	Number of product units purchased by the consumer on the purchase occasion t*.
PL	Set of indicators for private label brands.
$s_{ct,i}$	Indicator equal 1 if retail chain c was chosen by household i at purchase occasion t and 0 otherwise.
$S_{t,i}$	Vector of chain choice indicators $s_{ct,i}$ of household i up to purchase occasion t.
t, h	Indices for purchase occasion.
T_i	Number of purchases of household i during the sample period.
w_t	Week index for purchase occasion t.
$z_{jt,i}$	Indicator equal to 1 if brand j was available to household i at purchase occasion t and 0 otherwise.
Utility and its Determinants	
r	Risk aversion parameter*.
U_{jt}	Utility of brand j at purchase occasion t*.
X_{jt}	Utility determinants for brand j at purchase occasion t other than quality belief*.
β	Consumer's sensitivity parameters to utility determinants in X_{jt}*.
ε_{jt}	i.i.d. extreme value component of utility observed by the consumer, unobserved by the researcher*.
Quality and Quality Belief	
q_j	True quality of brand j*.
Q_{jt}	Quality belief of brand j on purchase occasion t*.
μ_{jt}	Mean quality belief of brand j on purchase occasion t*.
σ^2_{jt}	Uncertainty or variance in quality belief for brand j at purchase occasion t*.
Learning and Forgetting	
b	Parameter capturing the rate of forgetting*.
I_t	Consumer's information set at purchase occasion t*.

g_{jtm}	Consumption signal of one unit of brand j on purchase occasion t*.
G_{jt}	Average over a series of m_t consumption signals g_{jt} for brand j on purchase occasion t.
σ_g	Standard error of the consumption signal*.
Cross-Brand Learning	
P_{jkt}	Belief of similarity of brands j and k at purchase occasion t*.
P^*_{jkt}	P-value in the test made by the consumer when assessing brand similarity*.
φ	Ceiling parameter
κ	Contingency parameter
Household Heterogeneity	
v_b, ς_b	Mean and variance across households of the parameter b capturing the extent of forgetting, i.e. $b \sim \log-N(v_b, \varsigma_b)$.
v_{q_j}, ς_{q_j}	Mean and variance across households of the true quality parameter, i.e. $q_j \sim \log-N(v_{q_j}, \varsigma_{q_j})$
v_r, ς_r	Mean and variance across households of the risk aversion parameter, i.e. $r \sim \log-N(v_r, \varsigma_r)$
v_β, ς_β	Vectors of mean and variance across households of the parameters β, i.e. $\beta \sim N(v_\beta, \varsigma_\beta)$
$v_{\sigma_g}, \varsigma_{\sigma_g}$	Mean and variance across households of the standard error of the consumption signal, i.e. $\sigma_g \sim \log-N(v_{\sigma_g}, \varsigma_{\sigma_g})$
Other Notation	
Ω_i	Set of parameters, i.e. $\Omega_i = \{q_{j,i}, \beta_i, \sigma_{g,i}, b_i, r_i, \varphi, \kappa, \sigma_0^2\}$
$\tau=\{\tau_c\}$	Vector of chain-specific scaling parameter.

* The subscript i for consumers is dropped.

Estimation Issues

Identification. To obtain identification, we fix one of the true quality population mean parameters across households (i.e., $v_{q_j} = 0$ for j = National Brand 1), the uncertainty regarding brand quality at purchase occasion t = 0 (i.e., $\sigma_0^2 = 1$), and one of the chain-specific scale parameters (i.e., $\tau_c = 1$). The remaining parameters to be estimated can be summarized in the vector $\alpha \equiv \{v_{q_j}, \varsigma_{q_j}, v_{\beta_n}, \varsigma_{\beta_n}, v_{\sigma_g}, \varsigma_{\sigma_g}, v_b, \varsigma_b, v_r, \varsigma_r, \varphi, \kappa, \sigma_0^2, \tau_c\}$.

Dealing with left truncation. We do not observe consumers from the beginning of their consumption history and therefore face the problem of left truncation. Similar to previous authors (e.g., Mehta, Rajiv, and Srinivasan 2004), we include an initialization period. We first estimate the model with a subsample of 40 weeks and use the resulting $\mu_{jt,i}$ and $\sigma^2_{jt,i}$ to initialize the estimation of the remaining data. We set the initial quality beliefs at the beginning of the initialization period equal to the mean of the true quality across the population and, for identification (see above), fix the initial variance of the quality beliefs to 1, such that $\mu_{jt=0,i} = v_{q_j}$ and $\sigma_0^2 = 1$.

Likelihood function. For any consumer i, the likelihood of the entire purchase history $D_{T_i,i}$, conditional on $\{\Omega_i, \tau, \mathrm{E}_{T_i,i}, S_{T_i,i}\}$, is:

$$L_i\left(D_{T_i,i} \mid \Omega_i, \tau, \mathrm{E}_{T_i,i}, S_{T_i,i}\right) = \prod_{t=1}^{T_i} \prod_{j=1}^{J} \Pr\left(d_{jt,i} = 1 \mid \Omega_i, \tau, \mathrm{E}_{t,i}, S_{T_i,i}\right)^{d_{jt,i}}.$$

We denote the p.d.f. of parameters in Ω_i as $u_\Omega(\Omega_i)$ and the p.d.f. of $\mathrm{E}_{T_i,i}$ as $u_E(\mathrm{E}_{T_i,i})$. The unconditional likelihood of household's i purchase history $D_{T_i,i}$ is:

$$L_i\left(D_{T_i,i} \mid \alpha, S_{T_i,i}\right) = \int_{\Omega_i} \left(\int_{\mathrm{E}_{t,i}} L_i\left(D_{T_i,i} \mid \Omega_i, \tau, \mathrm{E}_{T_i,i}, S_{T_i,i}\right) u_E\left(\mathrm{E}_{T_i,i}\right) d\mathrm{E}_{T_i,i} \right) u_\Omega(\Omega_i) d\Omega_i.$$

Because this likelihood involves multidimensional integrals, numerical computation is prohibitively expensive. Therefore, in line with previous studies, we resort to simulated likelihood. Using F sets of scrambled Halton draws (Train 2003) for the coefficients in Ω_i and the consumption signals in $\mathrm{E}_{T_i,i}$, we obtain an estimate of L_i:

$$\hat{L}_i\left(D_{T_i,i} \mid \alpha, \tau, S_{T_i,i}\right) = \sum_{f}^{F} \left(L_i\left(D_{T_i,i} \mid \Omega^f, \tau, \mathrm{E}^f, S_{T_i,i}\right)\right).$$

We set F = 100, because larger values are not feasible given the computational demands of the model. As a robustness check, we run the model with different sets of draws, and the results do not change.

The log-likelihood for N households is:

$$LL\left(\left\{D_{T_i,i}\right\}_{i=1}^{N} \mid \alpha, S_{T_i,i}\right) = \sum_{i=1}^{N} \ln \hat{L}_i\left(D_{T_i,i} \mid \alpha, S_{T_i,i}\right).$$

We estimate the parameters in α by maximizing this likelihood:

$$\alpha_{MLE} = \arg\max_{\alpha} LL\left(\left\{D_{T_i,i}\right\}_{i=1}^{N} \mid \alpha, S_{T_i,i}\right).$$

Derivation of Equation [3.11]

The derivation of the lower part of Equation [3.11], that is, the variance of the quality belief for brand j at purchase occasion t in the presence of contingent cross-brand learning among PL brands, when PL brand k is purchased at time t – 1, is as follows.

We first introduce the following simplified notation:

$x = \mu_{jt-1}$,

$y = G_{kt}$,

$a = \text{var}(x) = \sigma_{jt-1}^2 * e^{b*(w_t - w_{t-1})}$, and

$b = \text{var}(y) = \dfrac{\sigma_g^2}{M_t}$.

Recall that $Cov(x, y) = 0$. When $d_{kt-1} = 1$ and $j \in PL$, we can write

$$\mu_{jt} = p\left(\frac{x}{a} + \frac{y}{b}\right)\left(\frac{1}{a} + \frac{1}{b}\right)^{-1} + (1 - p)x$$, and

$$\sigma_{jt}^2 = Var(\mu_{jt}) = Var\left(p\left(\frac{x}{a}+\frac{y}{b}\right)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1} + (1-p)x \right)$$

$$= Var\left(p\left(\frac{x}{a}+\frac{y}{b}\right)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1} \right) + Var((1-p)x) +$$

$$+2Cov\left(p\left(\frac{x}{a}+\frac{y}{b}\right)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1}, (1-p)x \right)$$

$$= p^2\left(\frac{1}{a}+\frac{1}{b}\right)^{-1} Var\left(\left(\frac{x}{a}+\frac{y}{b}\right)\right)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1} +$$

$$+(1-p)^2 Var(x) + 2p\left(\frac{1}{a}+\frac{1}{b}\right)^{-1} Cov\left(\left(\frac{x}{a}+\frac{y}{b}\right), x\right)(1-p)$$

$$= p^2\left(\frac{1}{a}+\frac{1}{b}\right)^{-2}\left[Var\left(\frac{x}{a}\right)+Var\left(\frac{y}{b}\right)+2Cov\left(\frac{x}{a},\frac{y}{b}\right)\right]+$$

$$+(1-p)^2 a + 2p(1-p)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1}\left[Cov\left(\frac{x}{a},x\right)+Cov\left(\frac{y}{b},x\right)\right]$$

$$= p^2\left(\frac{1}{a}+\frac{1}{b}\right)^{-2}\left[\frac{1}{a^2}Var(x)+\frac{1}{b^2}Var(y)+2\frac{1}{a}Cov(x,y)\frac{1}{b}\right]+$$

$$+(1-p)^2 a + 2p(1-p)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1}\left[\frac{1}{a}Var(x)+\frac{1}{b}Cov(y,x)\right]$$

$$= p^2\left(\frac{1}{a}+\frac{1}{b}\right)^{-2}\left[\frac{1}{a^2}a+\frac{1}{b^2}b+0\right]+(1-p)^2 a + 2p(1-p)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1}\left[\frac{1}{a}a+0\right]$$

$$= p^2\left(\frac{1}{a}+\frac{1}{b}\right)^{-1} + (1-p)^2 a + 2p(1-p)\left(\frac{1}{a}+\frac{1}{b}\right)^{-1}$$

$$= (1-p)^2 a + \left(\frac{1}{a}+\frac{1}{b}\right)^{-1}\left(p^2+2p(1-p)\right)$$

$$= (1-p)^2 a + \left(\frac{1}{a}+\frac{1}{b}\right)^{-1}\left(2p-p^2\right).$$

Hence, using the full notation:

if both $\sum_{\substack{k=1\\ k\in PL}}^{J} d_{kt-1} = 1$ and $j \in PL$

$$\sigma_{jt}^2 = \sum_{\substack{k=1\\ k\in PL}}^{J} d_{kt-1}\left((1-P_{jkt})^2 * \sigma_{jt-1}^2 * e^{b*(w_t-w_{t-1})} + \left(\frac{1}{\sigma_{jt-1}^2 * e^{b*(w_t-w_{t-1})}} + \frac{1}{\frac{\sigma_g^2}{M_t}} \right)^{-1} \left(2P_{jkt} - P_{jkt}^2\right) \right)$$

Appendix 3

TABLE A3.1 NOTATION OVERVIEW

Symbol	Description
Indices and (Vectors of) Indicators	
c, o	Index for copycat PL and original NB respectively
C, O	Indicator equal one for copycat PL and original NB respectively, 0 otherwise
d_{jt}	Indicator equal to 1 if brand j was consumed at purchase occasion t and 0 otherwise*.
$D_{t,i}$	Vector of purchase indicators d_{jt} of household i up to purchase occasion t.
$E_{t,i}$	Vector of consumption signal $G_{jt,i}$ received by household i up to purchase occasion t.
j, k	Indices for brand.
m	Index for unit of a product.
M_t	Number of product units purchased by the consumer on the purchase occasion t*.
t, h	Indices for purchase occasion.
T_i	Number of purchases of household i during the sample period.
u	Brand index, u=c for copycat PL and u=o for original NB
w_t	Week index for purchase occasion t.
$z_{jt,i}$	Indicator equal to 1 if brand j was available to household i at purchase occasion t and 0 otherwise.
Utility and its Determinants	
r	Risk aversion parameter*.
U_{jt}	Utility of brand j at purchase occasion t*.
X_{jt}	Utility determinants for brand j at purchase occasion t other than quality belief*.
β	Consumer's sensitivity parameters to utility determinants in X_{jt}*.
R_t	Reactance effect
ψ_u	Parameter capturing maximum potential magnitude of the reactance
τ_u	Parameter capturing rate of decrease of reactance related with the difference in brand quality beliefs
ε_{jt}	i.i.d. extreme value component of utility observed by the consumer, unobserved by the researcher*.
Quality and Quality Belief	
q_j	True quality of brand j*.
Q_{jt}	Quality belief of brand j on purchase occasion t*.
μ_{jt}	Mean quality belief of brand j on purchase occasion t*.
σ_{jt}^2	Uncertainty or variance in quality belief for brand j at purchase occasion t*.
Learning and Forgetting	
b	Parameter capturing the rate of forgetting*.
I_t	Consumer's information set at purchase occasion t*.
g_{jtm}	Consumption signal of one unit of brand j on purchase occasion t*.
G_{jt}	Average over a series of m_t consumption signals g_{jt} for brand j on purchase occasion t.

σ_g	Standard error of the consumption signal*.
Cross-Brand Learning	
φc	Perceived by the consumer probability that the consumption of original NB provides information about copycat PL
φo	Perceived by the consumer probability that the consumption of the copycat PL provides information about original NB
$\varphi^* u$	P-value in the test made by the consumer when assessing usefulness of cross-brand signals*.
η_u	Ceiling parameter, where u=c for copycat PL and u=o for original NB
κ_u	Contingency parameter
Household Heterogeneity	
v_b, ς_b	Mean and variance across households of the parameter b capturing the extent of forgetting, i.e. $b \sim \log - N(v_b, \varsigma_b)$.
v_{q_j}, ς_{q_j}	Mean and variance across households of the true quality parameter, i.e. $q_j \sim \log - N\left(v_{q_j}, \varsigma_{q_j}\right)$
v_r, ς_r	Mean and variance across households of the risk aversion parameter, i.e. $r \sim \log - N(v_r, \varsigma_r)$
v_β, ς_β	Vectors of mean and variance across households of the parameters β, i.e. $\beta \sim N(v_\beta, \varsigma_\beta)$
$v_{\sigma_g}, \varsigma_{\sigma_g}$	Mean and variance across households of the standard error of the consumption signal, i.e. $\sigma_g \sim \log - N\left(v_{\sigma_g}, \varsigma_{\sigma_g}\right)$
Other Notation	
Ω_i	Set of parameters, i.e. $\Omega_i = \{q_{j,i}, \beta_i, \sigma_{g,i}, b_i, r_i, \varphi, \kappa, \sigma_0^2\}$

* The subscript i for consumers is dropped.

Estimation Issues

Identification. The parameters to be estimated can be summarized in the vector $\alpha \equiv \left\{v_{q_j}, \varsigma_{q_j}, v_{\beta_n}, \varsigma_{\beta_n}, v_{\sigma_g}, \varsigma_{\sigma_g}, v_b, \varsigma_b, v_r, \varsigma_r, \varphi, \eta_u, \kappa, \psi_u, \tau_u, \sigma_0^2, \right\}$.$\varphi$, η_u, κ, ψ_u and τ_u

Dealing with left truncation. We do not observe consumers from the beginning of their consumption history and therefore face the problem of left truncation. Similar to previous authors (e.g., Mehta, Rajiv, and Srinivasan 2004), we include an initialization period. We first estimate the model with a subsample of 40 weeks and use the resulting $\mu_{jt,i}$ and $\sigma^2_{jt,i}$ to initialize the estimation of the remaining data. We set the initial quality beliefs at the beginning of the initialization period equal to the mean of the true quality across the population and, for identification (see above), fix the initial variance of the quality beliefs to 1, such that $\mu_{jt=0,i} = v_{q_j}$ and $\sigma_0^2 = 1$.

Likelihood function. For any consumer i, the likelihood of the entire purchase history $D_{T_i,i}$, conditional on $\{\Omega_i, \mathrm{E}_{T_i,i}\}$, is:

$$L_i\left(D_{T_i,i} \mid \Omega_i, \mathrm{E}_{T_i,i}\right) = \prod_{t=1}^{T_i}\prod_{j=1}^{J} \Pr\left(d_{jt,i} = 1 \mid \Omega_i, \mathrm{E}_{t,i}\right)^{d_{jt,i}} .$$

We denote the p.d.f. of parameters in Ω_i as $u_\Omega(\Omega_i)$ and the p.d.f. of $\mathrm{E}_{T_i,i}$ as $u_\mathrm{E}(\mathrm{E}_{T_i,i})$. The unconditional likelihood of household's i purchase history $D_{T_i,i}$ is:

$$L_i\left(D_{T_i,i} \mid \alpha\right) = \int_{\Omega_i}\left(\int_{\mathrm{E}_{t,i}} L_i\left(D_{T_i,i} \mid \Omega_i, \mathrm{E}_{T_i,i}\right) u_E\left(\mathrm{E}_{T_i,i}\right) d\mathrm{E}_{T_i,i}\right) u_\Omega\left(\Omega_i\right) d\Omega_i .$$

Because this likelihood involves multidimensional integrals, numerical computation is prohibitively expensive. Therefore, in line with previous studies, we resort to simulated likelihood. Using F sets of scrambled Halton draws (Train 2003) for the coefficients in Ω_i and the consumption signals in $\mathrm{E}_{T_i,i}$, we obtain an estimate of L_i:

$$\hat{L}_i\left(D_{T_i,i} \mid \alpha\right) = \sum_{f}^{F}\left(L_i\left(D_{T_i,i} \mid \Omega^f, \mathrm{E}^f\right)\right).$$

We set F = 100, because larger values are not feasible given the computational demands of the model. As a robustness check, we run the model with different sets of draws, and the results do not change.

The log-likelihood for N households is:

$$LL\left(\left\{D_{T_i,i}\right\}_{i=1}^{N} \mid \alpha\right) = \sum_{i=1}^{N} \ln \hat{L}_i\left(D_{T_i,i} \mid \alpha\right).$$

We estimate the parameters in α by maximizing this likelihood:

$$\alpha_{MLE} = \arg\max_{\alpha} LL\left(\left\{D_{T_i,i}\right\}_{i=1}^{N} \mid \alpha\right).$$

References

Aaker, David A. and Kevin Lane Keller (1990), "Consumer Evaluations of Brand Extensions," *Journal of Marketing*, 54 (1), 27-41.

AC Nielsen (2005), "Growth of Private Label Continues Worldwide, Says Acnielsen," AC Nielsen Global Systems.

AC Nielsen (2003), "The Power of Private Label: A Review of Growth Trends around the World."

Ackerberg, D. A. (2003), "Advertising, Learning, and Consumer Choice in Experience Good Markets: An Empirical Examination," *International Economic Review*, 44 (3), 1007-40.

---- (2001), "Empirically Distinguishing Informative and Prestige Effects of Advertising," *Rand Journal of Economics*, 32 (2), 316-33.

Ailawadi, K. L., K. Pauwels, and J. B. E. M. Steenkamp (2008), "Private-Label Use and Store Loyalty," *Journal of Marketing*, 72 (6), 19-30.

Ailawadi, Kusum L. (2001), "The Retail Power-Performance Conundrum: What Have We Learned?," *Journal of Retailing*, 77 (3), 299-318.

Ailawadi, Kusum L., Karen Gedenk, and Scott Neslin (2003a), "Title," Tuck Business School, Working Paper No. 03-16

Ailawadi, Kusum L. and B. Harlam (2004), "An Empirical Analysis of the Determinants of Retail Margins: The Role of Store-Brand Share," *Journal of Marketing*, 68 (1), 147-65.

Ailawadi, Kusum L. and Kevin Lane Keller (2004), "Understanding Retail Branding: Conceptual Insights and Research Priorities," *Journal of Retailing*, 80 (4), 331-42.

Ailawadi, Kusum L., Donald R. Lehmann, and Scott A. Neslin (2003b), "Revenue Premium as an Outcome Measure of Brand Equity," *Journal of Marketing*, 67 (4), 1-17.

Ainslie, A. and P. E. Rossi (1998), "Similarities in Choice Behavior across Product Categories," *Marketing Science*, 17 (2), 91-106.

Akcura, M. T., F. F. Gonul, and E. Petrova (2004), "Consumer Learning and Brand Valuation: An Application on over-the-Counter Drugs," *Marketing Science*, 23 (1), 156-69.

Anderson, John R. (1991), "The Adaptive Nature of Human Categorization," *Psychological Review*, 98 (3), 409-29.

Ataman, Berk, Harald van Heerde, and Carl Mela (2010), "The Long-Term Effect of Marketing Strategy on Brand Sales," *Journal of Research in Marketing*, forthcoming.

Balachander, Subramanian and Sanjoy Ghose (2003), "Reciprocal Spillover Effects: A Strategic Benefit of Brand Extensions," *Journal of Marketing*, 67 (1), 4-13.

Baltas, George, Peter Doyle, and Paul Dyson (1997), "A Model of Consumer Choice for National Vs. Private Label Brands," *Journal of the Operational Research*, 48 (10), 988-95.

Barbara Loken, Ivan Ross, and Ronald L. Hinkle (1986), "Consumer 'Confusion' of Origin and Brand Similarity Perceptions," *Journal of Public Policy and Marketing*5, 195-211.

Batra, Rajeev and Indrajit Sinha (2000), "Consumer-Level Factors Moderating the Success of Private Label Brands," *Journal of Retailing*, 76 (2), 175-91.

Bhat, S. and S. K. Reddy (2001), "The Impact of Parent Brand Attribute Associations and Affect on Brand Extension Evaluation," *Journal of Business Research*, 53 (3), 111-22.

Biehl, A. R. (2001), "Durable-Goods Monopoly with Stochastic Values," *Rand Journal of Economics*, 32 (3), 565-77.

Bonfrer, André and Pradeep K. Chintagunta (2004), "Store Brands: Who Buys Them and What Happens to Retail Prices When They Are Introduced?," *Review of Industrial Organization*, 24 (2), 195-218.

Boston Consulting Group (2004), "Private Label: Threat to Manufacturers, Opportunity for Retailers," The Boston Consulting Group.

Boush, David M., Shannon Shipp, Barbara Loken, Ezra Gencturk, Susan Crockett, Ellen Kennedy, Betty Minshall, Dennis Misurell, Linda Rochford, and Jon Strobel (1987), "Affect Generalization to Similar and Dissimilar Brand Extensions," *Psychology and Marketing*, 4 (Fall), 225-37.

Bradlow, E. T., Y. Hu, and T. H. Ho (2004), "A Learning-Based Model for Imputing Missing Levels in Partial Conjoint Profiles," *Journal of Marketing Research*, 41 (4), 369-81.

Brenner, Thomas (1999), Modelling Learning in Economics. Cheltenham: Edward Elgar.

Briesch, R. A., P. K. Chintagunta, and R. L. Matzkin (2002), "Semiparametric Estimation of Brand Choice Behavior," *Journal of the American Statistical Association*, 97 (460), 973-82.

Broniarczyk, S. M. and J. W. Alba (1994), "The Importance of the Brand in Brand Extension," *Journal of Marketing Research*, 31 (2), 214-28.

Bronnenberg, B. J., S. K. Dhar, and J. P. H. Dube (2009), "Brand History, Geography, and the Persistence of Brand Shares," *Journal of Political Economy*, 117 (1), 87-115.

Bronnenberg, B. J., J. P. Dube, C. F. Mela, P. Albuquerque, T. Erdem, B. Gordon, D. Hanssens, G. Hitsch, H. Hong, and B. H. Sun (2008), "Measuring Long-Run Marketing Effects and Their Implications for Long-Run Marketing Decisions," *Marketing Letters*, 19 (3-4), 367-82.

Burger, Philip.C. and Barbara Schott (1972), "Can Private Brand Buyers Be Identified?," *Journal of Marketing Research*, 9, 219-22.

Camacho, Nuno, Bas Donkers, and Stefan Stremersch (2008), "Predictably Non-Bayesian: Quantifying Salience Effects in Physician Learning," *Working Paper*.

Campbell, M. C. and A. Kirmani (2000), "Consumers' Use of Persuasion Knowledge: The Effects of Accessibility and Cognitive Capacity on Perceptions of an Influence Agent," *Journal of Consumer Research*, 27 (1), 69-83.

Campo, K. (1997), "Variety Seeking and the Sensitivity to in-Store Promotions," University of Antwerp-UFSIA.

Chen, Y. X. and S. Yang (2007), "Estimating Disaggregate Models Using Aggregate Data through Augmentation of Individual Choice," *Journal of Marketing Research*, 44 (4), 613-21.

Chintagunta, P., T. Erdem, P. E. Rossi, and M. Wedel (2006), "Structural Modeling in Marketing: Review and Assessment," *Marketing Science*, 25 (6), 604-16.

Chintagunta, Pradeep K. (2002), "Investigating Category Pricing Behavior at a Retail Chain," *Journal of Marketing Research*, 39 (2), 141-54.

Collins-Dodd, C. and J. L. Zaichkowsky (1999), "National Brand Responses to Brand Imitation: Retailers Versus Other Manufacturers," *The Journal of Product and Brand Management*, 8, 96-105.

Corstjens, Marcel and Rajiv Lal (2000), "Building Store Loyalty through Store Brands," *Journal of Marketing Research*, 37 (3), 281-91.

Cotterill, Ronald W., William P. Putsis, and Ravi Dhar (2000), "Assessing the Competitive Interaction between Private Labels and National Brands," *Journal of Business*, 73 (1), 109-37.

Crawford, G. S. and M. Shum (2005), "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica*, 73 (4), 1137-73.

Darby, Michael and Edi Karni (1973), "Free Competition and the Optimal Amount of Fraud," *Journal of Law & Economics*, 16 (1), 67-88.

Dekimpe, M. G., D. M. Hanssen, and J. M. Silva-Risso (1999), "Long-Run Effects of Price Promotions in Scanner Markets," *Journal of Econometrics*, 89 (1-2), 269-91.

Dekimpe, Marnik G. and D. M. Hanssens (1995), "Empirical Generalizations About Market Evolution and Stationarity," *Marketing Science*, 14 (3), G109-G21.

Dhar, R. and I. Simonson (2003), "The Effect of Forced Choice on Choice," *Journal of Marketing Research*, 40 (2), 146-60.

Dhar, S. K. and Stephen J. Hoch (1997), "Why Store Brand Penetration Varies by Retailer," *Marketing Science*, 16 (3), 208-27.

Dillard, J. P. and L. J. Shen (2005), "On the Nature of Reactance and Its Role in Persuasive Health Communication," *Communication Monographs*, 72 (2), 144-68.

Du , Rex, Eunkyu Lee, and Richard Staelin (2005), "Bridge, Focus, Attack, or Stimulate: Retail Category Management Strategies with a Store Brand," *Quantitative Marketing and Economics*, 3 (4), 393.

Du, Rex Y. and W. A. Kamakura (2006), "Household Life Cycles and Lifestyles in the United States," *Journal of Marketing Research*, 43 (1), 121-32.

Eckstein, Z. and K. I. Wolpin (1989), "The Specification and Estimation of Dynamic Stochastic Discrete Choice Models - a Survey," *Journal of Human Resources*, 24 (4), 562-98.

Erdem, T., M. P. Keane, and B. Sun (2008), "A Dynamic Model of Brand Choice When Price and Advertising Signal Product Quality," *Marketing Science*, 27 (6), 1111-25.

Erdem, Tülin (1996), "A Dynamic Analysis of Market Structure Based on Panel Data," *Marketing Science*, 15 (4), 359-78.

---- (1998), "An Empirical Analysis of Umbrella Branding," *Journal of Marketing Research*, 35 (3), 339-51.

Erdem, Tülin and M. P. Keane (1996), "Decision-Making under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science*, 15 (1), 1-20.

Erdem, Tülin and Baohong H. Sun (2002), "An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding," *Journal of Marketing Research*, 39 (4), 408-20.

Erdem, Tülin, Y. Zhao, and A. Valenzuela (2004), "Performance of Store Brands: A Cross-Country Analysis of Consumer Store-Brand Preferences, Perceptions, and Risk," *Journal of Marketing Research*, 41 (1), 86-100.

Fader, P. S. and B. G. S. Hardie (1996), "Modeling Consumer Choice among Skus," *Journal of Marketing Research*, 33 (4), 442-52.

Foxman, E.R., P.W. Berger, and J.A. (Cole (1992), "Consumer Brand Confusion: A Conceptual Framework," *Psychology and Marketing*, 9, 123-41.

Gijsbrechts, E., K. Campo, and P. Nisol (2000), "Towards a Theory-Based Measure of Purchase Variation," *Academy of Marketing Science Review*, Volume 2000 (06), 1-29.

Goettler, Ronald and Karen Clay (2009), "Tariff Choice with Consumer Learning and Switching Costs," *Working Paper*.

Groot, de Morris H. (1970), Optimal Statistical Decisions. New York: McGraw-Hill and Company.

Gurhan-Canli, Zeynep and Durairaj J. Maheswaran (1998), "The Effects of Extensions on Brand Name Dilution and Enhancement," *Journal of Marketing Research*, 35 (4), 464-73.

Hansen, K. and V. Singh (2008), "Are Store-Brand Buyers Store Loyal? An Empirical Investigation," *Management Science*, 54 (10), 1828-34.

Hansen, K., V. Singh, and P. Chintagunta (2006), "Understanding Store-Brand Purchase Behavior across Categories," *Marketing Science*, 25 (1), 75-90.

Hawkins, S. A. and Stephen J. Hoch (1992), "Low-Involvement Learning - Memory without Evaluation," *Journal of Consumer Research*, 19 (2), 212-25.

Heilman, C. M., D. Bowman, and G. P. Wright (2000), "The Evolution of Brand Preferences and Choice Behaviors of Consumers New to a Market," *Journal of Marketing Research*, 37 (2), 139-55.

Hoch, S. J. and Y. W. Ha (1986), "Consumer Learning from Advertising and the Ambiguity of Processing Experience," *Journal of Consumer Research*, 13 (2), 221– 33.

Hoch, Stephen J. (1996), "How Should National Brands Think About Private Labels?," *Sloan Management Review*, 37 (2), 89-102.

Hoch, Stephen J. and S. Banerji (1993), "When Do Private Labels Succeed," *Sloan Management Review*, 34 (4), 57-67.

Hoch, Stephen J. and J. Deighton (1989), "Managing What Consumers Learn from Experience," *Journal of Marketing*, 53 (2), 1-20.

Hoch, Stephen J., Alan L. Montgomery, and Young-Hoon Park (2006), "Title," Wharton School, University of Pennsylvania,

Howard, D. J., R. A. Kerin, and C. Gengler (2000), "The Effects of Brand Name Similarity on Brand Source Confusion: Implications for Trademark Infringement," *Journal of Public Policy & Marketing*, 19 (2), 250-64.

Inman, J. J., J. Park, and A. Sinha (2008), "A Dynamic Choice Map Approach to Modeling Attribute-Level Varied Behavior among Stockkeeping Units," *Journal of Marketing Research*, 45 (1), 94-103.

Israel, M. (2005), "Services as Experience Goods: An Empirical Examination of Consumer Learning in Automobile Insurance," *American Economic Review*, 95 (5), 1444-63.

Iyengar, R., A. Ansari, and S. Gupta (2007), "A Model of Consumer Learning for Service Quality and Usage," *Journal of Marketing Research*, 44 (4), 529-44.

Jacoby, J. and M. Morrin (1998), ""Not Manufactured or Authorized By...": Recent Federal Cases Involving Trademark Disclaimers," *Journal of Public Policy & Marketing*, 17 (1), 97-107.

Janakiraman, R., S. Dutta, C. Sismeiro, and P. Stern (2008), "Physicians' Persistence and Its Implications for Their Response to Promotion of Prescription Drugs," *Management Science*, 54 (6), 1080-93.

Johnson, J. P. and D. P. Myatt (2006), "On the Simple Economics of Advertising, Marketing, and Product Design," *American Economic Review*, 96 (3), 756-84.

Kahn, B. E. and J. S. Raju (1991), "Effects of Price Promotions on Variety-Seeking and Reinforcement Behavior," *Marketing Science*, 10 (4), 316-37.

Kapferer, J. N. (1995), "Brand Confusion - Empirical-Study of a Legal Concept," *Psychology & Marketing*, 12 (6), 551-68.

Kumar, Nirmalya and Jan-benedict E. M. Steenkamp (2007), Private Label Strategy: How to Meet the Store Brand Challenge. Boston: Harvard Business School Press.

Loken, Barbara and Deborah Roedder John (1993), "Diluting Brand Beliefs - When Do Brand Extensions Have a Negative Impact," *Journal of Marketing*, 57 (3), 71-84.

Lovett, Mitchell James (2008), "Unstable Consumer Learning Models: Structural Models and Experimental Investigation," Duke University.

Marketing News (1987), "Quality Creates Consumer Loyalty for Private Labels," in Marketing News Vol. 10.

McAlister, L. and E.A. Pessemier (1982), "Variety Seeking Behavior: An Interdisciplinary Review," *Journal of Consumer Research*, 9 (December), 311-22.

McCloskey, Michael E. and Sam Glucksberg (1978), "Natural Categories: Well Defined or Fuzzy Sets?," *Memory and Cognition*, 6 (4), 462-72.

McFadden, Daniel (1974), Conditional Logit Analysis of Qualitative Choice Behavior. New-York, London: Academic Press.

Mehta, Nitin, Surendra Rajiv, and Kannan Srinivasan (2004), "Role of Forgetting in Memory-Based Choice Decisions: A Structural Model," *Quantitative Marketing and Economics*, 2 (2), 107.

Meyvis, Tom and Cris Janiszewski (2004), "When Are Broader Brands Stronger Brands? An Accessibility Perspective on the Success of Brand Extensions," *Journal of Consumer Research*, 31 (2), 346-57.

Miller, Robert A. (1984), "Job Matching and Occupational Choice," *Journal of Political Economy*, 92 (6), 1086-120.

Mitra, D. and P. N. Golder (2006), "How Does Objective Quality Affect Perceived Quality? Short-Term Effects, Long-Term Effects, and Asymmetries," *Marketing Science*, 25 (3), 230-47.

Moberg, Anders (2006), "Speech by President and Ceo Anders Moberg," in 2006 Ahold Annual General Meeting. Amsterdam, the Netherlands.

Moeltner, K. and J. Englin (2004), "Choice Behavior under Time-Variant Quality: State Dependence Versus "Play-It-by-Ear" In Selecting Ski Resorts," *Journal of Business & Economic Statistics*, 22 (2), 214-24.

Narasimhan, Chakravarthi and Ronald T. Wilcox (1998), "Private Labels and the Channel Relationship: A Cross-Category Analysis," *Journal of Business*, 71 (4), 573-600.

Narayanan, S., P. K. Chintagunta, and E. J. Miravete (2007), "The Role of Self Selection, Usage Uncertainty and Learning in the Demand for Local Telephone Service," *Qme-Quantitative Marketing and Economics*, 5 (1), 1-34.

Narayanan, S. and P. Manchanda (2009), "Heterogeneous Learning and the Targeting of Marketing Communication for New Products," *Marketing Science*, Articles in Advance, pp. 1–18.

Narayanan, S., P. Manchanda, and Pradeep K. Chintagunta (2005), "Temporal Differences in the Role of Marketing Communication in New Product Categories," *Journal of Marketing Research*, 42 (3), 278-90.

Nelson, Phillip (1970), "Information and Consumer Behavior," *Journal of Political Economy*, 78 (1970), 311-29.

Nijs, V. R., Marnik G. Dekimpe, Jan-Benedict E. M. Steenkamp, and D. M. Hanssens (2001), "The Category-Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1-22.

Nijs, V. R., S. Srinivasan, and K. Pauwels (2007), "Retail-Price Drivers and Retailer Profits," *Marketing Science*, 26 (4), 473-87.

Park, C. W., S. Milberg, and R. Lawson (1991), "Evaluation of Brand Extensions - the Role of Product Feature Similarity and Brand Concept Consistency," *Journal of Consumer Research*, 18 (2), 185-93.

Pechmann, C. and S. Ratneshwar (1992), "Consumer Covariation Judgments - Theory or Data Driven," *Journal of Consumer Research*, 19 (3), 373-86.

Planet Retail (2007), "Private Label Trends Worldwide " *e-intelligence on global retailing, www.planetretail.net* (July).

PlanetRetail (2007), "Private Label Trends Worldwide " *e-intelligence on global retailing, www.planetretail.net* (July).

Pullig, C., C. J. Simmons, and R. G. Netemeyer (2006), "Brand Dilution: When Do New Brands Hurt Existing Brands?," *Journal of Marketing*, 70 (2), 52-66.

Quick, Brain, L. and Michael T. Stephenson (2007), "Further Evidence That Psychological Reactance Can Be Modeled as a Combination of Anger and Negative Cognitions," *Communication Research*, 34x, 255-76.

Richardson, Paul S. (1997), "Are Store Brands Perceived to Be Just Another Brand?," *Journal of Product and Brand Management*, 6 (5), 388-404.

Richardson, Paul S., A. S. Dick, and A. K. Jain (1994), "Extrinsic and Intrinsic Cue Effects on Perceptions of Store Brand Quality," *Journal of Marketing*, 58 (4), 28-36.

Roberts, John and Glenn Urban (1988), "Modeling Multiattribute Utility, Risk and Belief Dynamics for New Consumer Durable Brand Choice," *Management Science*, 34 (February), 167–85.

Sayman, S. and J. S. Raju (2004), "Investigating the Cross-Category Effects of Store Brands," *Review of Industrial Organization*, 24 (2), 129-41.

Sayman, Serdar, Stephen J. Hoch, and Jagmohan S. Raju (2002), "Positioning of Store Brands," *Marketing Science*, 21 (4), 378-97.

Scott-Morton, Fiona S. and Florian Zettelmeyer (2004), "The Strategic Positioning of Store Brands in Retailer-Manufacturer Negotiations," *Review of Industrial Organization*, 24 (2), 161-94.

Shin, Sangwoo, Sanjog Misra, and Dan Horsky (2007), "Disentangling Preferences, Inertia and Learning in Brand Choice Models," *Working Paper*.

Simonson, Itamar (1994), "Trademark Infringement from the Buyer Perspective: Conceptual Analysis and Measurement Implications," *Journal of Public Policy & Marketing*, 13 (2), 181-200.

Steenkamp, Jan-Benedict E. M. and Marnik G. Dekimpe (1997), "The Increasing Power of Store Brands: Building Loyalty and Market Share," *Long Range Planning*, 30 (6), 917-30.

Steenkamp, Jan-Benedict, E.M. (1990), "Conceptual Model of the Quality Perception Process," *Journal of Business Research*, 21, 309-33.

Stigler, George J. (1961), "The Economics of Information," *Journal of Political Economy*, 69, 213.

Swait, Joffre and Jordan Louviere (1993), "The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit-Models," *Journal of Marketing Research*, 30 (3), 305-14.

Swaminathan, Vanitha, R. J. Fox, and S. K. Reddy (2001), "The Impact of Brand Extension Introduction on Choice," *Journal of Marketing*, 65 (4), 1-15.

Train, Kenneth (2003), Discrete Choice Methods with Simulation. Cambridge: Cambridge University Press.

Trivedi, Minakshi and Michael Morgan (2003), "Promotional Evaluation and Response among Variety Seeking Segments," *Journal of Product and Brand Management*, 12 (6), 408-23.

van der Lans, R., R. Pieters, and M. Wedel (2008), "Competitive Brand Salience," *Marketing Science*, 27 (5), 922-31.

Van Heerde, H., K. Helsen, and M. G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230-45.

Van Horen, Femke, Rik Pieters, and Didrik. A. Stapel (2008), "Unexpected Benefits of Being Less Rather Than More Similar: How Mindset and Brand Presentation Influence Copycat Evaluation," in Association for Consumer Research Annual Conference. San Francisco, USA.

Warlop, L. and J. W. Alba (2004), "Sincere Flattery: Trade-Dress Imitation and Consumer Choice," *Journal of Consumer Psychology*, 14 (1-2), 21-27.

Warlop, L., S. Ratneshwar, and S. M. J. van Osselaer (2005), "Distinctive Brand Cues and Memory for Product Consumption Experiences," *International Journal of Research in Marketing*, 22 (1), 27-44.

Wright, A. A. and J. G. Lynch (1995), "Communication Effects of Advertising Versus Direct Experience When Both Search and Experience Attributes Are Present," *Journal of Consumer Research*, 21 (4), 708-18.

Zaichkowsky, Judith Lynne and Richard Neil Simpson (1996), "The Effect of Experience with a Brand Imitator on the Original Brand,",*Marketing Letters*, 7 (1), 31-39.

Zeithaml, Valarie A. (1988), "Consumer Perceptions of Price, Quality, and Value - a Means-End Model and Synthesis of Evidence," *Journal of Marketing*, 52 (3), 2-22.

Samenvatting (Summary in Dutch)

De groei van de informatie economie (Nelson 1970; Stigler 1961) heeft ervoor gezorgd dat onderzoekers in economie (e.g. Johnson and Myatt 2006; Miller 1984) en bedrijfskunde (e.g. Eckstein and Wolpin 1989; Narayanan and Manchanda 2009) de aandacht focussen op onzekerheid en leerprocessen tijdens beslissingen. Veel onderzoekers bestuderen met name hoe personen eigenschappen van het beslissingsobject leren, bijvoorbeeld hoe consumenten het niveau van productattributen leren. Een groeiend aantal onderzoeken laat zien dat keuzes niet gebaseerd zijn op de werkelijke situatie, maar meer op de perceptie hiervan. Bovendien bestaat er onzekerheid over deze percepties, hetgeen voor risicomijdende beslissers leidt tot lager nut van objecten. Deze onzekerheid kan gereduceerd worden wanneer beslissers leren (of verhoogd worden wanneer beslissers vergeten). Dit leerproces en met name hoe dit proces de perceptie over objecten vormt en de daaropvolgende beslissingen staan centraal in dit proefschrift.

De Bayesiaanse formulering voor leren is een gebruikelijke aanpak om leerprocessen te modelleren in bedrijfskundig en economisch onderzoek (Erdem and Keane 1996; Miller 1984; Roberts and Urban 1988). Deze formulering beschrijft hoe consumenten hun a priori percepties over objecten integreren met nieuwe informatiesignalen, gebruikmakende van de regel van Bayes, en wordt vaak geïntegreerd in keuzemodellen voor deze objecten. In de kwantitatieve marketing, Bayesiaanse leermodellen zijn toegepast op verschillende interessante problemen die variëren in welke individuen leren, welke dimensies van objecten zij leren, en de informatiebronnen die zij gebruiken. Het leerobject is doorgaans de kwaliteit van een merk en de informatiebron is consumptie. Dit proefschrift past in deze onderzoeksstroom: het focust op hoe de consumptie van merken consumenten in staat stelt te leren over de kwaliteit van merken en vervolgens de keuze voor merken beïnvloedt.

Het is belangrijk om vast te stellen dat de meerderheid van het voorgaande onderzoek zich bezighoudt met leerprocessen binnen een merk – oftewel, hoe informatie behorende bij een specifiek merk de perceptie over ditzelfde merk verandert. Echter, er zijn situaties waarbij de kwaliteit van een merk ook informatie bevat over de kwaliteit van andere merken. Dit kan gebeuren wanneer consumenten merken categoriseren in dezelfde “mental category”, of wanneer merken attributen delen die door consumenten als diagnostisch gezien worden (Janakiraman et al. 2008). In deze situaties kunnen consumenten nieuwe informatie over een merk, bijvoorbeeld door consumptie ervaringen over dit merk, gebruiken om de kwaliteitspercepties van een ander merk aan te passen. Deze leerprocessen tussen merken is conceptueel vergelijkbaar met spillover effecten tussen attributen binnen hetzelfde merk (Bradlow et al. 2004), tussen producten van hetzelfde merk in dezelfde categorie (Balachander and Ghose 2003), en tussen producten van hetzelfde merk in verschillende categorieën (Erdem 1998; Erdem and Sun 2002). Hoewel deze laatste leerprocessen redelijk goed gedocumenteerd zijn, hebben leerprocessen tussen verschillende merken nauwelijks aandacht gekregen in de literatuur, met uitzondering van een recent onderzoek door Janakiraman et al. (2008) dat leerprocessen tussen originele medicijnen en hun generieke versies bestudeert. Dit is een belangrijke tekortkoming in de literatuur, omdat spillover effecten tussen merken door consumptie ervaringen aanzienlijke gevolgen hebben voor het managen van merken die substantieel verschillen van principes gebaseerd op leerprocessen binnen merken.

De belangrijkste bijdragen van dit proefschrift liggen op het gebied van leerprocessen tussen verschillende merken. In het bijzonder, we onderzoeken leereffecten tussen merken en huismerken van consumer packaged goods (zoals supermarkt producten). Huismerken, oftewel het eigen merk van een winkelier, zijn ten opzichte van A-merken van fabrikanten geleidelijk in populariteit toegenomen in de laatste decennia en hebben op dit moment een substantieel marktaandeel: 16% in de VS (AC Nielsen 2005), 39.6% in Groot Brittannië en 46% in Zwitserland (Planet Retail 2007 p.7). Verkoop van huismerken levert winkeliers hogere marges op (Ailawadi and Harlam 2004), verbetert de machtsverhoudingen met fabrikanten (Ailawadi 2001), en verbetert de concurrentiepositie ten opzichte van prijsvechters (Boston Consulting Group 2004). Het succes van huismerken vormt een uitdaging voor A-merken, die vroeger de packaged goods markt domineerde (Steenkamp and Dekimpe 1997).

Onderzoek naar huismerken benadrukt het belang van de gepercipieerde kwaliteit om de vraag naar huismerken te bepalen (Ailawadi et al. 2003a; Dhar and Hoch 1997; Hoch and Banerji 1993; Steenkamp and Dekimpe 1997). Niet alleen het niveau van de gepercipieerde kwaliteit van het huismerk speelt een rol, maar ook de mate van onzekerheid hierover (Batra and Sinha 2000; Erdem et al. 2004). Hoewel het belang van consumenten percepties over de kwaliteit van huismerken bekend is, is minder bekend hoe consumenten deze vormen, met name wanneer het gaat om leerprocessen, hetgeen huismerken onderscheidt van A-merken.

In dit proefschrift onderzoeken wij twee situaties van leerprocessen tussen merken waarbij huismerken een rol spelen. Ten eerste onderzoeken we consumptie spillovers tussen huismerken van verschillende (concurrende) winkeliers, die op een zelfde manier gepercipieerd kunnen worden door consumenten (Ailawadi 2001; Richardson 1997). Ten tweede, bestuderen we de aard en de impact van op consumptie gebaseerde leerprocessen tussen een leidend A-merk en een copycat huismerk dat de verpakking imiteert (Kapferer 1995; Sayman et al. 2002; Scott-Morton and Zettelmeyer 2004).

Dit proefschrift bestaat uit vijf hoofdstukken. Hoofdstuk 2 bestudeert de factoren en de mate van leereffecten binnen merken in verschillende product categorieën. Dit hoofdstuk introduceert het Bayesiaanse leermodel als onderdeel van de merkkeuze formulering. We kalibreren dit huishouden specifieke model op de aankoopdata uit 20 verschillende productcategorieën. We verkrijgen categorie- en huishoudenspecifieke schattingen van parameters die de mate aangeven waarmee consumenten percepties aanpassen op basis van nieuwe op consumptie gebaseerde informatie. Dit hoofdstuk geeft inzichten in de algemeenheid en grootte van leereffecten voor fastmoving consumer goods, de variatie in leerprocessen tussen categorieën en huishoudens en de onderliggende factoren. We laten zien dat leereffecten optreden en significant zijn in bijna alle categorieën, en tegelijkertijd in sterkte variëren tussen categorieën en huishoudens. Het is interessant om te zien dat correlaties tussen leereffecten van huishoudens in verschillende categorieën erg laag zijn, hetgeen aangeeft dat kennis vergaard door consumptie niet een eigenschap van een huishouden is. Tegelijkertijd vinden we dat leereffecten negatief gerelateerd zijn aan de mate waarin consumenten op zoek zijn naar variatie, positief aan de gepercipieerde risico in de categorie en de mate waarin de categorie als duur wordt ervaren, en sterker optreden bij consumenten die regelmatig aankopen doen in de categorie – waarnemingen die op basis van de bestaande literatuur valide zijn.

Terwijl hoofdstuk 2 een bekend proces beschrijft (leerprocessen binnen een merk), gebruikmakende van een bestaande methodologie (Bayesiaans aanpassen van kwaliteitspercepties op basis van herhaaldelijk consumeren van hetzelfde merk) met als doel empirisch bewijs te vergroten en onderliggende factoren te onderzoeken, is de belangrijkste bijdrage van dit proefschrift te vinden in hoofdstukken drie en vier. In deze hoofdstukken bestuderen we leerprocessen tussen verschillende merken, hetgeen nog niet onderzocht is. In deze hoofdstukken ontwikkelen we nieuwe hypothesen en geven empirisch bewijs gebruikmakende van verbeterde leermodellen. De gemeenschappelijke aanpak in deze hoofdstukken is dat consumenten ervaringen van een bepaald merk gebruiken om de kwaliteitspercepties van andere merken aan te passen, en minstens een van deze merken is altijd een huismerk. Naast deze overeenkomsten, behandelen deze hoofdstukken hele andere situaties met verschillende uitdagingen en bevindingen voor winkeliers en fabrikanten.

In hoofdstuk drie bestuderen we leerprocessen tussen huismerken van verschillende winkeliers. Het doel van dit onderzoek is om twee verschillende inzichten van wetenschappers en managers over huismerken te integreren. Het eerste inzicht is dat winkeliers huismerken gebruiken om zich te onderscheiden van concurrerende winkeliers. Het tweede, tegengestelde inzicht gaat ervan uit dat huismerken "geen merken" (generieke merken) zijn en dat consumenten geen verschil zien tussen huismerken van verschillende winkelketens. Onze aanname is dat consumenten tot op zekere hoogte leren tussen huismerken van verschillende winkelketens. We verwachten dat leerprocessen tussen huismerken gemodereerd wordt door de gepercipieerde kwaliteitsovereenkomsten tussen huismerken, waarbij kleinere (grotere) overeenkomsten leiden tot zwakkere (sterkere) leereffecten tussen huismerken van concurrerende winkelketens. Bovendien verwachten we dat deze leereffecten tussen huismerken veranderen over de tijd, wanneer consumenten preciezere percepties over de kwaliteit van ieder huismerk ontwikkelen. Om deze verwachtingen te toetsen, breiden we het traditionele Bayesiaanse leermodel uit om leereffecten tussen huismerken te beschrijven afhankelijk van de gepercipieerde overeenkomsten tussen huismerken. We maken gebruik van scannerdata van afwasmiddelen waarin we de keuzes van huishoudens voor verschillende wasmiddelen observeren en de gebruikte marketingactiviteiten in de tijd. Aangezien wij geïnteresseerd zijn in leerprocessen tussen huismerken van verschillende winkelketens, richten we ons alleen op huishoudens die afwasmiddelen kopen in minstens twee verschillende winkelketens. We gebruiken ons model om te bepalen hoe consumenten de kwaliteit van een merk leren door consumptie, in welke mate consumenten leren tussen huismerken, en hoe dit beïnvloedt wordt door gepercipieerde overeenkomsten tussen huismerken.

Onze resultaten laten substantiële leereffecten zien tussen verschillende huismerken. Gepercipieerde overeenkomsten tussen huismerken beïnvloeden deze effecten significant, maar leerprocessen tussen merken worden pas irrelevant wanneer huismerken substantieel van elkaar verschillen. In simulaties illustreren we de implicaties van deze leerprocessen tussen huismerken. We laten zien dat gepercipieerde overeenkomsten tussen huismerken de mogelijkheden van winkeliers om zich te differentiëren vermindert in de ogen van consumenten die boodschappen doen in meerdere winkels. Tegelijkertijd vinden we dat leereffecten tussen huismerken kan leiden tot een toename in het marktaandeel ten opzichte van A-merken. Dit komt doordat leereffecten tussen huismerken ervoor zorgen dat de onzekerheid in een huismerk gereduceerd kan worden door consumptie van een ander huismerk, hetgeen leidt tot een toename van het nut. Deze bevindingen zijn interessant voor winkeliers. Wanneer winkeliers huismerken gebruiken om zich de differentiëren van andere ketens, dan worden zij geadviseerd een zeer hoge kwaliteit van huismerken te ontwikkelen ten opzichte van de concurrentie. Echter, hierdoor verliezen zij de voordelen van de leereffecten tussen verschillende huismerken hetgeen helpt marktaandeel te winnen van A-merken.

Hoofdstuk 4 bestudeert leereffecten tussen een A-merk en een huismerk die het A-merk probeert te imiteren door de verpakking na te maken (oftewel een “copycat” huiswerk). Dit hoofdstuk bestudeert of het succes van een “copycat” huismerk toe te schrijven is aan de imitatie strategie. Hoewel copycats veelvuldig voorkomen, zijn de effecten over de tijd op het geïmiteerde merk onduidelijk aangezien er weinig empirisch bewijs beschikbaar is over de gevolgen op merkkeuze. Bovendien is de generaliseerbaarheid van onderzoek naar copycats beperkt omdat de meeste onderzoeken zich richten op bijna letterlijke kopieën waarbij ook de merknaam geïmiteerd wordt. Het effect van zulke imiteerstrategieën wordt voornamelijk bepaald door verwarring over het merk bij consumenten (Warlop and Alba 2004). Echter, ‘copycat’ huismerken zijn zelden letterlijke kopieën: zij hebben andere merkennamen, en hoewel de verpakkingen vergelijkbaar zijn, is het verschil met het geïmiteerde merk duidelijk zichtbaar. Zo’n imitatie strategie leidt zelden tot verwarring bij consumenten (Warlop and Alba 2004). Tegelijkertijd kan het wel leerprocessen tussen het A-merk en het ‘copycat’ huismerk veroorzaken. Aan de ene kant kunnen positieve consumptie ervaringen met het geïmiteerde A-merk leiden tot hogere kwaliteitspercepties van het ‘copycat’ huismerk, hetgeen leidt tot een verhoging van het marktaandeel van het ‘copycat’ huismerk ten opzichte van het A-merk. Aan de andere kant kan de copycat strategie ook negatieve effecten hebben voor de winkelier. Het verschil in kwaliteit tussen het A-merk en het ‘copycat’ huismerk kan leiden tot contrast effecten, hetgeen de evaluatie van het A-merk verhoogt – het zogenoemde “beloningseffect” (Zaichkowsky and Simpson 1996). Of, consumenten zien de copycat strategie van het huismerk als een manier van de winkelier om hen te misleiden, hetgeen kan leiden tot een “weerstand effect”

Om de potentie van deze copycat strategieën te achterhalen, specificeren wij een Bayesiaans leermodel dat leerprocessen van een merk en tussen een A-merk en een ‘copycat’ merk beschrijft. Dit model kwantificeert mogelijke weerstand- en beloningseffecten. We kalibreren heb model op data van twee productcategorieën, wasmiddelen en afwasmiddelen in twee verschillende winkelketens. Onze resultaten laten zien of een ‘copycat’ huismerk een ‘vriend’ van het geïmiteerde A-merk is (oftewel, het beloningseffect of weerstand effect treedt op), of een ‘vijand’ (wanneer het ‘copycat’ merk marktaandeel steelt van het A-merk). Onze resultaten laten zien dat het effect van de copycat strategie op merkkeuze gedomineerd wordt door leereffecten van het originele A-merk naar het ‘copycat’ huismerk. Dit resulteert in een reductie van de onzekerheid over de kwaliteitsperceptie van het ‘copycat’ huismerk en verhoogt de kans om gekozen te worden door risicomijdende consumenten. Deze toename in marktaandeel voor het ‘copycat’ huismerk gaat met name ten koste van het originele A-merk, en houdt zelfs stand nadat consumenten zich realiseren wat de werkelijke kwaliteit van het ‘copycat’ huismerk is – hetgeen impliceert dat ‘copycat’ huismerken met name een ‘vijand’ van originele A-merken zijn.

Hoofdstukken twee, drie en vier presenteren gedetailleerde onderbouwingen van bovengenoemde resultaten. Ieder hoofdstuk presenteert een conceptueel model van het te bestuderen probleem, en beschrijft de data en het model. Ieder hoofdstuk bevat ook een paragraaf met praktische implicaties. In hoofdstuk vijf, het concluderende hoofdstuk van dit proefschrift, integreren we de verschillende resultaten en plaatsen we deze in een breder perspectief. We identificeren ook de beperkingen van het onderzoek die leiden tot nieuwe onderzoeksideeën die interessant zijn voor toekomstig onderzoek.

Streszczenie (Summary in Polish)

Wraz z rozwojem ekonomi informacji (Nelson 1970; Stigler 1961) uwaga badaczy z dziedziny ekonomii (np. Johnson i Myatt 2006; Miller 1984) i biznesu (np. Eckstein i Wolpin 1989; Narayanan i Manchanda 2009) skupiła się na roli jaką odgrywają niepewność i uczenie się w decyzjach podejmowanych przez podmioty gospodarcze, np. konsumentów lub firmy. Badania skupiły się głownie na uczeniu się przez podejmujących decyzje o właściwościach przedmiotu decyzji, na przykład cechach wybieranych przez konsumenta produktów. Mniej uwagi poświecono innym formom uczenia się, takim jak na przykład zdobywanie umiejętności. Bogaty i wciąż rosnący zbiór badan wskazuje, że istotne przy tłumaczeniu i przewidywaniu decyzji ekonomicznych jest wzięcie pod uwagę, że nie są one podejmowane na podstawie faktycznego stanu rzeczy ale raczej na podstawie wyobrażeń podejmujących decyzje o stanie rzeczywistości. Te wyobrażenia o wybieranych przedmiotach może charakteryzować niepewność, co w przypadku unikających ryzyka podmiotów prowadzi do spadku oczekiwanej użyteczności tych przedmiotów. Niepewność zmniejsza się w miarę uczenia i rośnie w miarę zapominania. Te procesy, i ich wpływ na wyobrażenia i wybory konsumentów są głównym tematem niniejszej pracy doktorskiej.

Popularnym w literaturze ekonomicznej podejściem do modelowania procesu uczenia jest model bayesowski (Erdem i Keane 1996; Miller 1984; Roberts i Urban 1988). Model ten jest matematyczną reprezentacją przedstawiającą uczenie się jako proces integrowania nowych informacji z wcześniej posiadana wiedzą. Model bayesowski jest często używany jako część większego modelu wyboru spośród alternatyw lub modelu incydencji. W badaniach marketingowych, model beyesowski został zastosowany w wielu różnych kontekstach, dotyczących różnych podmiotów gospodarczych, obiektów uczenia, charakterystyk opisujących te obiekty które są przedmiotem uczenia, i źródeł informacji. Najszerzej badane jest uczenie się konsumentów o jakości marek w którym źródłem informacji jest bezpośrednia konsumpcja. Niniejsza praca, wpisuje się w ten nurt badań.

Większość badań w tej dziecinie skupia się na uczeniu „wewnątrz marki”, to jest wiedza o marce jest aktualizowana na podstawie wiadomości pochodzących od tej jednej marki. Jednak jest możliwe, że konsumenci wierzą, że informacja o jednej marce zawiera informacje o innych markach. Taka sytuacja może mieć miejsce np. gdy konsumenci grupują marki w kategorie semantyczne, lub gdy zespół marek ma wspólne cechy które są widoczne dla konsumentów i postrzegane jako przydatne w przewidywaniu jakości marki (Janakiraman et al. 2008). W takim kontekście konsumenci mogą używać nowych informacji pochodzących od jednej marki do aktualizowania wyobrażenia o innej marce. Takie między-markowe uczenie wydaje się podobne pod względem teoretycznym do uczenia pomiędzy charakterystykami pojedynczego produktu (Bradlow et al. 2004), pomiędzy różnymi produktami tej samej branży i marki (Balachander i Ghose 2003), i pomiędzy produktami tej samej marki w rożnych branżach (Erdem 1998; Erdem i Sun 2002). Podczas gdy powyższe rodzaje uczenia są udokumentowane, wciąż wiemy niewiele o uczeniu między-markowym. Jednym z niewielu badan na ten temat jest raport Janakiraman et al. (2008) który studiuje uczenie pomiędzy oryginalnym lekiem i jego generyczną kopią. Temat uczenia między-markowego zasługuje na uwagę ze względu na jego znaczący wpływ na sukces marek.

Głównym zamierzeniem tej pracy jest poszerzyć nasze zrozumienie uczenia między-markowego. Proces ten jest studiowany w kontekście marek sprzedawców w branży dóbr codziennego użytku. Marki sprzedawców, które często odróżnia się w literaturze od marek producentów, stopniowo, na przestrzeni ostatnich kilkudziesięciu lat, zyskują na popularności i obecnie stanowią znaczącą cześć wartości sprzedanych dóbr codziennego użytku, na przykład 16% w USA (AC Nielsen 2005), 39.6% w Wielkiej Brytanii i 46% w Szwajcarii (Planet Retail 2007 p.7). Sprzedaż własnych marek umożliwia sprzedawcom uzyskanie większej marży (Ailawadi i Harlam 2004), wzmocnić pozycję negocjacyjną względem producentów (Ailawadi 2001), i być bardziej konkurencyjnym względem sprzedawców dyskontowych (Boston Consulting Group 2004). Wzrost marek sprzedawców stanowi wyzwanie dla marek producentów (Steenkamp i Dekimpe 1997).

Badania wskazują, że kluczowym czynnikiem akceptacji marek sprzedawców przez konsumentów jest ich postrzegana jakość (Ailawadi et al. 2003a; Dhar i Hoch 1997; Hoch i Banerji 1993; Steenkamp i Dekimpe 1997). Ważną role odgrywa nie tylko poziom jakości ale również stopień niepewności w opiniach konsumentów (Batra i Sinha 2000; Erdem et al. 2004). Podczas gdy rola postrzeganej jakości jest dobrze udokumentowana, mniej badań ukazuje jak konsumenci budują swoje wyobrażenia. Głównie jeżeli chodzi o procesy uczenie się które są bardziej prominentne w przypadku marek sprzedawców niż marek producentów.

Niniejsza praca bada dwa różne rodzaje uczenia między-markowego mającego miejsce w przypadku marek sprzedawców. Pierwszy to uczenie pomiędzy różnymi markami należącymi do różnych, konkurujących ze sobą sprzedawców, a które to marki mogą być postrzegane przez konsumentów jako jedna kategoria semantyczna (Ailawadi 2001; Richardson 1997). Drugi typ studiowanego uczenia między-markowego, to uczenie pomiędzy kopiowaną marką producenta a kopiującą jej wygląd marką sprzedawcy (Kapferer 1995; Sayman et al. 2002; Scott-Morton i Zettelmeyer 2004).

Niniejsza praca zawiera pięć rozdziałów. Rozdział pierwszy to wstęp. Rozdział drugi mierzy prędkość i determinanty uczenia się konsumentów w szerokiej gamie branż produktów codziennego użytku. Rozdział ten stanowi punkt wyjścia dla kolejnych rozdziałów jako, że model w nim użyty jest standardowym modelem uczenia się bayesowskiego „wewnątrz marki" który jest następnie rozwinięty w kolejnych rozdziałach. Model uczenia jest zagnieżdżony w modelu wyboru alternatywy i skalibrowany na danych o wyborach marek dokonywanych przez indywidualne gospodarstwa domowe w 20 branżach. Model estymuje między innymi parametry wyrażające szybkość uczenia, to jest relatywna wagę przywiązywaną do nowych informacji względem wcześniej posiadanej wiedzy. Miara ta jest pozyskana dla każdego gospodarstwa domowego i w każdej branży z osobna. Wyniki wskazują, że dla większości gospodarstw domowych uczenie się jest istotne statystycznie i ma ekonomicznie istotny wpływ na wybory konsumentów, występuje duża różnorodność w tempie uczenia pomiędzy gospodarstwami i branżami. Co ciekawe, korelacja w prędkości uczenia się pomiędzy różnymi branżami dla poszczególnych gospodarstw jest bardzo mała co sugeruje, że uczenie się o jakości marek nie jest stabilną cechą konsumentów. Dalsza analiza wyników wskazuje, że uczenie jest wolniejsze w kontekstach gdzie dla konsumentów ważna jest różnorodność marek, a szybsza droższych branżach i w tych w których dane gospodarstwo dokonuje wielu zakupów, oraz w przypadku gdy konsumenci bardziej unikają ryzyka.

Najistotniejsze rozdziały tej pracy to rozdział trzeci i czwarty. Prezentują one nowe w literaturze hipotezy, rozwijają metodologie konieczną aby je przetestować, a także dokonują takiego testu. Wspólnym elementem tych rozdziałów jest to, że studiują one między-markowe uczenie na podstawie konsumpcji.

Rozdział trzeci bada czy proces między-markowego uczenia zachodzi dla marek różnych sprzedawców. Celem badania jest powiązanie dwóch sposobów postrzegania marek sprzedawców jaki jest obecny w literaturze akademickiej i wśród menadżerów. Pierwszy sposób uczenia się utrzymuje, że marki są narzędziem które sprzedawcy mogą wykorzystać do odróżnienia się od konkurencyjnych sprzedawców. Drugi sposób uczenia widzi marki sprzedawców jako „nie-marki", generyczne produkty nie rozróżniane przez konsumentów. Rozdział prezentuje hipotezę, że konsumenci generalizują wiedzę z jednej marki sprzedawców do innych marek sprzedawców, że ten proces jest silniejszy w przypadku marek postrzeganych jako podobne. Aby przetestować te hipotezy tradycyjny model bayesowski jest rozszerzony o uczenie między-markowe którego szybkość, zależy od postrzeganego podobieństwa pomiędzy markami. Model jest estymowany przy użyciu danych o zakupach gospodarstw domowych w branży płynnych detergentów do mycia naczyń. Dane, oprócz wyborów marek dokonanych przez konsumentów zawierają dane o czynnościach marketingowych marek, takich jak cena i promocje.

Rezultaty potwierdzają hipotezy i wskazują na wysoki poziom uczenia między-markowego. Prędkość uczenia zależy od postrzeganego podobieństwa ale różnica w prędkości uczenia pomiędzy najbardziej podobnymi i najmniej podobnymi markami w naszych danych jest dla większości gospodarstw domowych znikoma.

Przeprowadzone symulacje obrazują znaczenie uzyskanych wyników. Pokazujemy, że między-markowe uczenie powoduje, że marki sprzedawców w niewielkim stopniu przyczyniają się do zróżnicowania konkurujących sprzedawców w opinii konsumentów . Jednocześnie symulacje pokazują, że dzięki między-markowemu uczeniu marki sprzedawców moja zwiększyć swój udział w rynku względem marek producentów. Dzieje się tak dlatego, że uczenie między-markowe redukuje niepewność co do jakości marek sklepowych i przez to zwiększa ich oczekiwaną użyteczność. Te wyniki sugerują, że sprzedawcy chcący użyć swoich marek do odróżnienia się od konkurencyjnych sprzedawców powinni upozycjonować swoją markę jako produkt zdecydowanie wyższej jakości niż inni sprzedawcy, tak aby różnica w jakości była postrzegana jako większa niż ma to miejsce obecnie. Jednak taka strategia ma wadę jako, że nie czerpie ona korzyści płynących z uczenia między-markowego w postaci zmniejszonej niepewności konsumentów .

Rozdział czwarty przenosi uwagę z uczenia między markami sprzedawców, na uczenie pomiędzy imitowaną marką producenta a imitującą wygląd jej opakowania marką sprzedawcy. Mimo, że imitowanie wyglądu opakowania lub produktu jest powszechnym zjawiskiem, niewiele badan rozpatruje jaki jest efekt takiej praktyki na wybory konsumentów , szczególnie w rzeczywistym kontekście, nie w laboratorium. Ponadto nie jest jasne czy dotychczasowe wyniki dotyczące kopiowania wyglądu aplikują się do marek sprzedawców gdyż większość uwagi była poświecona imitacjom, to jest bardzo podobnym kopia oryginalnych produktów, często imitującym oprócz wyglądu również nazwę marki. Wpływ na konsumentów w takich przypadkach jest spowodowany tym, ze mylą oni markę kopiowaną i kopiującą (Warlop i Alba 2004). Inaczej jest w przypadku marek sprzedawców które rzadko są dosłownymi kopiami oryginalnych marek. Przeważnie maja one nazwę która nie nawiązuje do oryginału, a podobieństwo opakowania, choć jest bezdyskusyjne również jest łatwo dostrzegalne. Taki sposób imitowania rzadko prowadzi do pomylenia marek (Warlop i Alba 2004). Możliwe jest natomiast, że prowadzi on do między-markowego uczenia. Gdyby tak było to z jednej strony pozytywne doświadczenia z oryginalną marką mogą przynieść korzyści kopiującej marce sprzedawcy i spowodować przejecie przez markę kopiującą udziału w rynku marki oryginalnej. Jednak z drugiej strony strategia kopiowania może okazać się obosiecznym mieczem dla sprzedawcy. Jeżeli różnica w jakości pomiędzy oryginałem i kopia doprowadzi do efektu kontrastu ocena oryginalnej marki może wzrosnąć – tak zwany „efekt nagrody" (Zaichkowsky i Simpson 1996). Jest także możliwe, że konsumenci zinterpretują podobieństwo opakowania jako próbę zwiedzenia ich, prowadziłoby to do „efektu buntu" przeciw kopiującej marce (Warlop i Alba 2004).

Aby ocenić efekt kopiowania niniejsza praca rozszerza przedstawiony w rozdziale trzecim model bayesowskiego uczenia w taki sposób, że oprócz uczenia wewnątrz marki, pomiędzy markami, oryginalną i kopiującą, model uwzględnia efekty nagrody i buntu. Model jest estymowany używając dwóch zestawów danych, każdy dotyczy innej branży, detergentów do odzieży i naczyń, i innych sprzedawców. Wyniki wskazują czy kopie oryginalnych marek są „przyjaciółmi" tych ostatnich (wywołując pozytywne dla nich efekty nagrody lub buntu) czy „wrogami" (przejmując ich reputacje i udział w rynku).

Uzyskane rezultaty sugerują, że kopiowanie wyglądu przez marki sprzedawców prowadzi do jednostronnego uczenia się konsumentów – jedynie w kierunku od oryginału do kopii, to jest informacje o oryginalnej marce wpływają na opinie o jej kopii. Taki proces prowadzi do redukcji niepewności dotyczącej jakości marki kopiującej i w konsekwencji do zwiększenia jej udziału w rynku, głownie kosztem oryginalnej marki. Efekt ten utrzymuje się nawet wtedy gdy konsumenci orientują się, jaka jest rzeczywista jakość marki kopiującej. Oznacza to, że kopiujące marki sprzedawców są „wrogami" ich oryginalnych odpowiedników.

Rozdziały drugi, trzeci i czwarty opisują szczegółowo powyższe wyniki. Ponadto każdy z tych rozdziałów przedstawia teoretyczny model studiowanego zagadnienia, prezentuje użyte dane i opisuje model empiryczny oraz wnioski dla menedżerów. Rozdział piaty, zamykający niniejszą pracę, dokonuje przeglądu wszystkich wyników i dyskutuje w jaki sposób poszerzają one naszą wiedzę. Rozdział omawia również ograniczenia niemniejszej pracy oraz problemy i pytania które powinny być tematem badan w przyszłości.